Introduction 000	Modelling 00000	The Extended Kalman Filter 0000	Methodology	Conclusion

Center of mass compensation of a nanosatellite testbed based on the Extended Kalman Filter

R. C. Silva, S. Battistini, R. A. Borges, C. Cappelletti

University of Brasília

rcsilva@lara.unb.br, simone.battistini@aerospace.unb.br, chantal@aerospace.unb.br, raborges@ene.unb.br

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Introduction 000	Modelling 00000	The Extended Kalman Filter 0000	Methodology	Conclusion

Overview

- Introduction
 - Testbed overview
- 2 Modelling
 - Dynamic equations and variable definitions
 - Kinematic equation
 - Augmented state equation
 - Reference system
 - The LAICA testbed parameters
- 3 The Extended Kalman Filter
 - Filter equations
 - Filter equations
 - The DF/Dx jacobian
 - Complex Step Differentiation
 - Methodology
- 5 Results

Introduction ●00	Modelling 00000	The Extended Kalman Filter 0000	Methodology	Conclusion
Testbed overview				

Testbed characteristics

Technical specifications

• Hardware

- IMU (3-axis mag, gyro and accel)
- 3 Movable Mass Units
- Embedded μ controller
- 3 Reaction wheels

Structure

- Air bearing
- Helmholtz cage

Figure: LAICA nanosatellite testbed.



Introduction 000	Modelling 00000	The Extended Kalman Filter	Methodology	Conclusion
Testbed overview				
The bala	ncing pr	oblem		

Some facts

- Although limited in the roll and pitch axis to $\pm 45^{\circ}$, the testbed has 3 rotational Degrees of Freedom (DOF);
- Considering the testbed is not a symmetrical rigid body, its mass distribution results in a Center of Mass (CM) displaced from its Center of Rotation (CR);
- This displacement results in a undesirable torque which affects the actuation system.

Solution?

Discovering the exact position of the Center of Mass (CM) and controlling its position by moving some masses on the testbed.

Introduction	Modelling 00000	The Extended Kalman Filter 0000	Methodology	Conclusion
Testbed overview				

The balancing problem

How is it done?

In this work, in order to discover the position of the Center of Mass (CM), the testbed is excited with the torque generated by the reaction wheels mounted on it. Then, with the knowledge of this input torque and measuring the angular velocities performed by the testbed during this operation, the Extended Kalman Filter (EKF) is used in order to estimate the testbed parameters given by **R**, the CM offset vector, and **J**, the inertia tensor given by a 3×3 matrix.



Figure: 3-axis setup of reaction wheels

Introduction 000	Modelling ●○○○○	The Extended Kalman Filter 0000	Methodology	Conclusion
Dynamic equations a	nd variable definitio	ns		

Rigid body dynamics

Euler equation

$$\frac{\partial \mathbf{H}}{\partial t} = \mathbf{J}\dot{\omega} + \omega \times \mathbf{J}\omega + (\dot{\mathbf{h}} + \omega \times \mathbf{h}) = \mathbf{R} \times m\mathbf{g}_{\mathbf{b}} + \mathbf{T}$$
,

- J the inertia tensor of the whole system
- $\bullet~$ H total angular momentum of the system
- ullet h momentum generated by the reaction wheels
- *m* the total mass of the system
- T the total external torque disturbances
- R the CM offset vector
- $\mathbf{g}_{\mathbf{b}}$ the local gravity (in body frame)

Introduction 000	Modelling ○●○○○	The Extended Kalman Filter 0000	Methodology	Conclusion
Kinematic equation				

Kinematic equation

Euler rates for the ZYX (or 3-2-1) rotation sequence

[ģ]		[1	$ extsf{sin}(\phi) \cdot extsf{tan}(heta)$	$cos(\phi) \cdot tan(heta)$		$\left[\omega_{x} \right]$	
$\dot{\theta}$	=	0	$\mathit{cos}(\phi)$	-sin(heta)	.	ω_y	(2)
Ļ $\dot{\psi}$]		0	$\mathit{sin}(\phi)/\mathit{cos}(heta)$	$cos(\phi)/cos(heta)$		$\left\lfloor \omega_z \right\rfloor$	

- $\bullet~\phi$ roll angle of the testbed
- θ pitch angle of the testbed
- $\bullet \ \psi$ yaw angle of the testbed
- $\omega_{\rm x}$ angular velocity of the testbed in the body x-axis
- ω_y angular velocity of the testbed in the body y-axis
- ω_z angular velocity of the testbed in the body z-axis

Introduction 000	Modelling ○○●○○	The Extended Kalman Filter 0000	Methodology	Conclusion
Augmented state equ	Jation			

Augmented State Equation

The **x** state vector

- For the EKF algorithm, the state of the system is selected as being $\mathbf{x}_1 = [\omega_x \ \omega_y \ \omega_z]^T$.
- Using the joint state equation procedure, the state is augmented to $\mathbf{x} = [\mathbf{x_1} \ \mathbf{x_2}]^T$, where $\mathbf{x_2} = [J_x \ J_y \ J_z \ J_{xy} \ J_{xz} \ J_{yz} \ mR_x \ mR_y \ mR_z]^T$.
- Since x₂ contains the parameters to be estimated, which are constant, the joint state equation becomes:

$$\dot{\mathbf{x}} = \begin{bmatrix} \dot{\mathbf{x}_1} \\ \dot{\mathbf{x}_2} \end{bmatrix} = F(\mathbf{x}_1, \mathbf{x}_2, \mathbf{u}) = \begin{bmatrix} f(\mathbf{x}_1, \mathbf{x}_2, \mathbf{u}) \\ 0 \end{bmatrix}, \quad (3)$$

where
$$f(\mathbf{x}_1, \mathbf{x}_2, \mathbf{u}) = \dot{\omega} = J^{-1}(J\omega \times \omega + R \times m\mathbf{g} - (\dot{\mathbf{h}} + \omega \times \mathbf{h}))$$
 and $\mathbf{u} = -(\dot{\mathbf{h}} + \omega \times \mathbf{h})$.

Introduction 000	Modelling ○○○●○	The Extended Kalman Filter 0000	Methodology	Conclusion
Reference system				

Rotation Sequence

The ZYX or 321 sequence



Figure: Inertial frame (centered at the CR of the Air Bearing).



Figure: Body frame (centered at the CR of the Air Bearing, but fixed to the testbed).

Introduction 000	Modelling ○○○○●	The Extended Kalman Filter 0000	Methodology	Conclusion
The LAICA testbe	d parameters			

Inertia tensor, mass and unbalance vector

Table: Testbed parameters used in the simulation.

$J(kg\cdot m^2)^1$				Mass (kg)	Unbalance vector ² $(10^{-3}m)$
	0.265	0	0]		T
	0	0.246	0	14.307	
	L O	0	0.427		

Table: Standard deviation of the noise in the gyro readings

Body axis	Standard deviation (rad/s)
Х	0.0026
Y	0.0049
Z	0.0031

 1 The Inertia Tensor (J) and the Mass (m) of the platform values in the table are the same as those estimated for the actual testbed.

²The shown values for the unbalance vector components were arbitrarily assumed for the simulation (a reasonable value based on previous experiments). (a = b + a = b) = -2a

R. C. Silva, S. Battistini, R. A. Borges, C. Ca

Introduction 000	Modelling 00000	The Extended Kalman Filter ●○○○	Methodology	Conclusion
Filter equations				

Simulation of the dynamic and kinematic equations

$$\begin{vmatrix} \phi \\ \dot{\theta} \\ \dot{\psi} \end{vmatrix} = \mathbf{A}(\phi, \theta, \psi)_{\mathbf{3} \times \mathbf{3}} \cdot \mathbf{x}_{\mathbf{1}}$$
(4)

$$\begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix}_{pew} = \begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix}_{old} + \mathbf{A}(\phi, \theta, \psi)_{\mathbf{3} \times \mathbf{3}} \cdot \mathbf{x}_{\mathbf{1}} \cdot dt$$
(5)

$$\dot{\mathbf{x}}_{1} = J^{-1}(J\mathbf{x}_{1} \times \mathbf{x}_{1} + R \times m\mathbf{g} - (\dot{\mathbf{h}} + \mathbf{x}_{1} \times \mathbf{h}))$$
(6)

$$\mathbf{x}_{new} = \mathbf{x}_{old} + \dot{\mathbf{x}} \cdot dt \tag{7}$$

$$z = H \cdot x + w, \tag{8}$$

where w is the measurement noise, dt is the step size, which was selected as 0.0001s and the measurement matrix H is given by $H = [I_{3\times3} \ 0_{3\times9}]^T$.

Introduction 000	Modelling 00000	The Extended Kalman Filter ○●○○	Methodology	Conclusion
Filter equations				

Execution of the filter equations

$$F = \frac{D\mathbf{F}}{D\mathbf{x}}\Big|_{\hat{\mathbf{x}}} + [I]_{12 \times 12} \tag{9}$$

$$\dot{P} = F \cdot P + P \cdot F^{T} + L \cdot Q \cdot L^{T} - P \cdot H^{T} / R \cdot H \cdot P$$
(10)

$$P_{new} = P_{old} + \dot{P} \cdot dt \tag{11}$$

$$K = P \cdot H^T \cdot R^{-1} \tag{12}$$

$$\hat{\dot{x}} = \begin{bmatrix} \hat{\mathbf{x_1}} \\ \mathbf{0}_{6\times 1} \end{bmatrix}$$
(13)

$$\begin{bmatrix} \mathbf{0}_{3\times 1} \end{bmatrix}$$

$$\dot{x}_{new} = \dot{x}_{old} + K \cdot (z - H \cdot \dot{x}) \tag{14}$$

$$\hat{\mathbf{x}}_{new} = \hat{\mathbf{x}}_{old} + \hat{\dot{\mathbf{x}}} \cdot dt \tag{15}$$

æ



The $\frac{D\mathbf{F}}{D\mathbf{x}}$ jacobian is a 12×12 matrix given by

$$\frac{D\mathbf{F}}{D\mathbf{x}} = \begin{bmatrix} \frac{\partial F_1}{\partial x_1} & \cdots & \frac{\partial F_1}{\partial x_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial F_{12}}{\partial x_1} & \cdots & \frac{\partial F_{12}}{\partial x_{12}} \end{bmatrix} = [A_{ij}]_{12 \times 12} = \begin{bmatrix} \frac{\partial F_i}{\partial x_j} \end{bmatrix}_{12 \times 12}, \ i, j \in \{1, ..., 12\}$$
(16)

and, after simplification,

$$\frac{D\mathbf{F}}{D\mathbf{x}}\Big|_{\hat{\mathbf{x}}} = \begin{bmatrix} \frac{\partial F}{\partial \omega} & \frac{\partial F}{\partial \mathbf{J}} & \frac{\partial F}{\partial m\mathbf{R}} \\ & \mathbf{0}_{9\times 12} \end{bmatrix}\Big|_{\hat{\mathbf{x}}} , \qquad (17)$$

where $\frac{\partial F}{\partial \omega}$, $\frac{\partial F}{\partial J}$ and $\frac{\partial F}{\partial mR}$ are 3 × 3, 3 × 6 and 3 × 3 matrices, respectively.

Introduction 000	Modelling 00000	The Extended Kalman Filter ○○○●	Methodology	Conclusion
Complex Step Differe	ntiation			

Complex Step Differentiation idea for the $\frac{DF}{dx}$ calculation

The numerical differentiation problem

One simple discrete method for numerical differentiation is given by

$$\frac{df}{dx} \approx \frac{f(x+h) - f(x)}{h}$$
, where h is the step size. (18)

However, when the step size h becomes too small, the procedure results in erratic values, mainly as consequence of subtraction errors.

Solution? Complex step differentiation!

Through complex step differentiation, the same differentiation may be accomplished using the approximation

$$\frac{df}{dx} \approx \frac{Im[f(x+ih)]}{h}$$
, where *i* is given by $i^2 = -1$. (19)

R. C. Silva, S. Battistini, R. A. Borges, C. Ca

Introduction 000	Modelling 00000	The Extended Kalman Filter 0000	Methodology	Conclusion
<u> </u>				

Simulation and initial parameters

The procedure for running the EKF is given by the following steps:

- The simulator is configured with the testbed known parameters (the ground truth parameters).
- The dynamic model is simulated. The torque generated by the reaction wheels and initial conditions of the testbed are given as input. The simulator outputs the angular velocities of the testbed.
- Noises are added to these angular velocities signals to simulate real measurement conditions.
- With only the knowledge of these input and output signals, the EKF algorithm is executed. The estimated $\hat{x_2}$ vector is collected after the algorithm converges.
- Sestimated x₂ parameters are compared with the ground truth x₂ parameters.

Introduction 000	Modelling 00000	The Extended Kalman Filter 0000	Methodology	Results	Conclusion
Results					

Figure: Convergence of the estimated inertia tensor components.



R. C. Silva, S. Battistini, R. A. Borges, C. Ca

Introduction 000	Modelling 00000	The Extended Kalman Filter 0000	Methodology	Results	Conclusion
Results					

Figure: Unbalance vector components³ (dashed = real, continuous = estimated).



³The graph shows the unbalance components scaled by the *m* factor (testbed mass) \sim

R. C. Silva, S. Battistini, R. A. Borges, C. Ca

EKF Balancing

Introduction 000	Modelling 00000	The Extended Kalman Filter 0000	Methodology	Results	Conclusion
Results					

Within 5 secs the error between the known (ω_z) and the estimated $(\hat{\omega_z})$ angular velocities stays in the $\approx \pm 0.001 rad/s$ range.



Figure: Evolution of the difference $\omega_z - \hat{\omega_z}$

Introduction 000	Modelling 00000	The Extended Kalman Filter	Methodology	Conclusion
Conclusi	ons			

- This work presented a testbed being developed at the LAICA laboratory in the University of Brasília for testing attitude determination and control systems (ADCS) of nanosatellites, *e.g.* CubeSATs.
- The balancing problem was presented, as well as the modelling for one solution for this problem, based on reaction wheel actuation and on the use of the Extended Kalman Filter.
- The results shown indicate that the proposed method is adequate for solving the balancing problem.
- Future works include discretizing the EKF and embedding it on the board computer of the real testbed.