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Continuous Time Estimation of Pilot Biodynamic Response for Vertical Bounce Coupling Assessment

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Abstract. This work addresses the estimation of time-varying pilot parameters within Rotorcraft–Pilot Couplings. An analytical, physics-based model with the minimum number of degrees of freedom represents the coupled pilot–helicopter dynamics. Parameter tracking uses sigma-points filtering to capture time-varying parameter characterization. Simulations under diverse conditions accurately reconstruct the trajectories of states and parameters in real time. The approach provides a practical basis for robust online identification and control strategies to mitigate Pilot-Assisted Oscillations.

Introduction

The helicopter's vibrations, inherent to rotor–airflow interactions, degrade controllability and overall safety. Pilots experience these effects as reduced control authority. Pilots' performances decrease while workload increases [1,2].

In the context of interactions between pilot biomechanics and helicopter vibratory dynamics, known as (adverse) Rotorcraft–Pilot Couplings (RPCs) [1,3], this work is focused in the 2–8 Hz range, which lies outside the pilot's intentional control bandwidth; in this regime, the pilot's biomechanical response becomes the driver of a closed-loop behavior.

Following Venrooij's framework [4], the input-output relation is defined as Biodynamic Feedthrough (BDFT). This specific case studies the vertical collective bounce [3], an RPC where vertical excitation couples with collective-lever motion through pilot biomechanics, forming a feedback loop. Since the collective lever controls the main rotor thrust, this loop can enter a self-excited limit cycle, making it one of the critical RPC phenomena to be mitigated.

Several pilot–helicopter models have been developed to capture RPC dynamics [4,5]. An analytical, physics-based approach is adopted in [6], with the minimum number of degrees of freedom and parameters, and benchmarked against prior studies and validated references. These models aim to provide interpretable representations without any loss of information about the phenomenon. The objective is to clarify how physics and geometry non-linearities shape the dynamic response.

These models simplify the parameters' tuning relative to higher order models and preserve a direct link between parameter modifications and system response. The reduced parameters set helps the deployment in control and estimation frameworks with efficient real-time execution; moreover, the provided kinematic models can be exploited for inference even in the absence of input information.

Problem

Biomechanical systems exhibit intrinsic time variance due to fatigue or sudden events. Accordingly, their parameters cannot be assumed constant over time [7]. The governing laws are not known a priori, and such variability may trigger Pilot-Assisted Oscillations (PAOs).

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The goal is to identify parameters' evolution without an explicit model or direct measurements, selecting at each instant the most plausible parameters set to enable interpretation and mitigation via informed and robust control schemes, without sacrificing controllability.

Estimating time-varying parameterization is widespread across disciplines. Among others, see the work by [8, 9].

The task is inherently complex: online parameter evolution requires simultaneous state and parameter estimation. Even a simple relation $\dot{x} = w(t)\, x(t)$ becomes nonlinear here, since both w(t) and x(t) are jointly unknown and must be estimated [8]. , a probabilistic and optimization approach is adopted. The helicopter-focused literature remains limited [7], especially on sigma-point framework, which uses deterministic sampling for statistically robust linearization [9]. Two approaches are considered [8, 9], with the latter's core scheme presented.

Algorithm 1. Sigma-points Parameter Filter

Require prior $\hat{\mathbf{w}}_0 = E[\mathbf{w}]$, $\mathbf{P}_{w,0} = E[(\mathbf{w} - \hat{\mathbf{w}}_0)(\mathbf{w} - \hat{\mathbf{w}}_0)']$
for k = 1, 2, … **do**
  $\hat{\mathbf{w}}_k^- \leftarrow \hat{\mathbf{w}}_{k-1}$, $\mathbf{P}_{w,k}^- \leftarrow \mathbf{P}_{w,k-1} + \mathbf{R}_{k-1}^w$
  $\mathbf{S}_{w,k} \leftarrow \mathrm{chol}(\mathbf{P}_{w,k}^-)$
  $\mathcal{W}_{k|k-1} = [\hat{\mathbf{w}}_k^-,\ \hat{\mathbf{w}}_k^- \pm \gamma\, \mathbf{S}_{w,k}]$
  $\mathcal{D}_{k|k-1} \leftarrow G(x_k, \mathcal{W}_{k|k-1})$
  $\mathbf{d}_k \leftarrow \sum_i \mathbf{W}_i^{(m)} \mathbf{D}_{i,k|k-1}$
  $\mathbf{P}_{dd,k} \leftarrow \sum_i \mathbf{W}_i^{(c)} (\mathbf{D}_{i,k|k-1} - \mathbf{d}_k)(\mathbf{D}_{i,k|k-1} - \mathbf{d}_k)' + \mathbf{R}_k^e$
  $\mathbf{P}_{wd,k} \leftarrow \sum_i \mathbf{W}_i^{(c)} (\mathbf{W}_{i,k|k-1} - \hat{\mathbf{w}}_k^-)(\mathbf{D}_{i,k|k-1} - \mathbf{d}_k)'$
  $\mathbf{K}_k \leftarrow \mathbf{P}_{wd,k}\, \mathbf{P}_{dd,k}^{-1}$
  $\hat{\mathbf{w}}_k \leftarrow \hat{\mathbf{w}}_k^- + \mathbf{K}_k(\mathbf{d}_k - \mathbf{d}_k)$, $\mathbf{P}_{w,k} \leftarrow \mathbf{P}_{w,k}^- - \mathbf{K}_k\, \mathbf{P}_{dd,k}\, \mathbf{K}_k'$
end for

The problem is decoupled [8]: a state estimation step and a parameter identification step are executed separately at each time step. This strategy lowers computational cost, and often allows each sub-problem to be treated as linear, unlike the joint formulation, [8]. In the absence of a known parameter-evolution model, each parameter follows a random walk, enabling probabilistic exploration of the parameter's space at every step. Future work will consider richer dynamics while addressing hyperparameter selection. In general, the problem can be written as:

$$\left(\begin{aligned} \dot{x} &= f\big(x(t), u(t); w(t)\big) + v_x(t), \\ \dot{w} &= g\big(x(t), w(t)\big) + v_w(t), \\ y &= h\big(x(t), w(t)\big) + v_y(t). \end{aligned}\right)$$

Here f is the state dynamics of x, g is the parameter dynamics of w, h is the observation map for y, and v_x, v_x, v_γ are the process and measurement noise. Multiple formulations were considered: first, a second-order system to estimate both physical parameters and the state-space entries of A (a simple black-box setup).; subsequently, a formulation from prior work [6] was adopted, reported below:

$$\left[\ell^2\left(\eta^2 m_e + m_p\right) + J_\ell\right]\ddot{\theta} + \left[c_p \ell^2 cos^2\dot{\theta} + c_o\right]\dot{\theta} + \left[\ell g\left(m_e + m_p\right) - \ell^2 k_p sin\theta\right)cos\theta + \ell^2 k_p sin\theta cos\theta$$
$$+k_o\theta - k_o\hat{\theta} = -\ell\left(m_e + m_p\right)cos\theta\ddot{z}$$

Where θ is the angle between the collective axis and the floor, $[\theta, \dot{\theta}]$ are the states; ℓ the lever length; η the Center of Mass relative position; m_l, $m_p(t)$ the lever and pilot equivalent mass; J_l the lever inertia; $c_p(t)$, c_o the equivalent damping; $k_p(t)$, k_o the equivalent stiffness; $\hat{\theta}$, $\bar{\theta}$ the spring preloads; and $\ddot{z}$ the base vertical acceleration. Parameters to be identified: $[m_p, c_p, k_p]$.

Simple linear systems are modeled as mass–spring–damper equivalents and can be written in two standard forms:

$$\begin{bmatrix} \dot{\theta} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & -\frac{c}{m} \end{bmatrix} \begin{bmatrix} \theta \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \ddot{z}$$

The goal is to estimate both state-space coefficients $[a_{21}(t), a_{22}(t), b_{21}(t)]$ and physical parameters $[m_p(t), c_p(t), k_p(t)]$, which enter the equations through nonlinear terms. Despite its simplicity, the single Degree of Freedom (1-DOF) model yields a statistically grounded linearization at each step, enabling effective use of measurements, unlike purely deterministic differentiation. Equation (2), though the simplest in [6], already embeds the key nonlinearities, making it a suitable benchmark for parameter identification. Future work will extend to 2-DOF (linear and nonlinear) models as proxies for complex multibody systems, enabling rigorous model-mismatch tests. The observation model is a direct state measurement [8]; future work will include richer sensor dynamics. Algorithms from [8] (a Dual Extended Kalman Filter with recursive state-parameter coupling) and from [9] (a sigma-points Kalman filter) were tested. The latter proved to be more robust via implicit statistical linearization; therefore, the square-root Central Difference Kalman Filter (additive-noise form) of [10] is adopted. To drive parameter covariance, two options are used: Robbins–Monro adaptation and annealing of a preset constant matrix. Future work will estimate process and measurement noise online, reducing reliance on offline tuning, following [11].

Results

Several systems with distinct dynamics were simulated via an Euler–Maruyama step for stochastic dynamics and excited with inputs ranging from simple accelerations of the base to identification-oriented force signals. Noise was varied in both the process and the measurement channels.

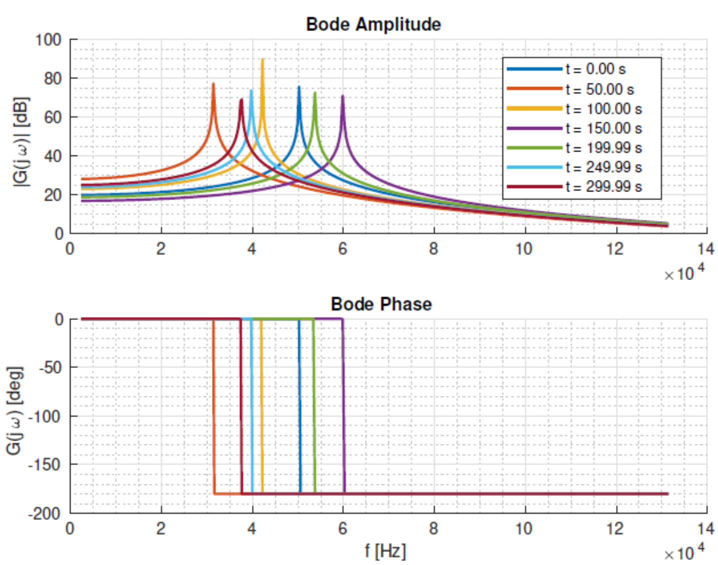

Figura 1: Time Variant Bode Graphs.

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Evolving parameter dynamics produce distinct frequency-domain responses. Identifying the transfer function through linear or physics-based models enables characterization of system behavior and detection of deviation from nominal dynamics, informing control strategies to maintain robust stability (object of future work).

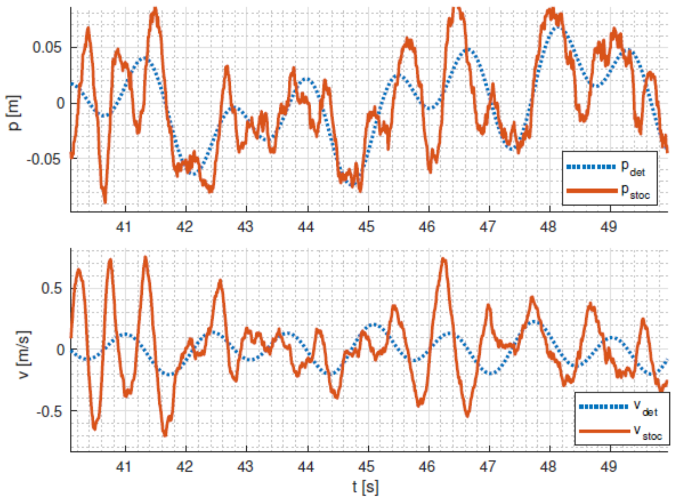


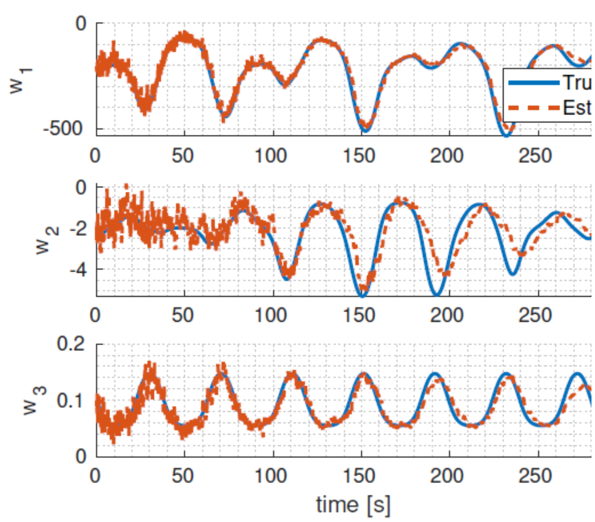
Figura 2: Linear System Process Noise.

Here, the excitation profiles and the corresponding simulations of the system dynamics are shown

Results for selected noise levels show simultaneous reconstruction of the state and time-varying parameters. The main challenge is the lack of a direct measurement map for parameters such as equivalent mass, damping, and stiffness, which are not directly measurable.

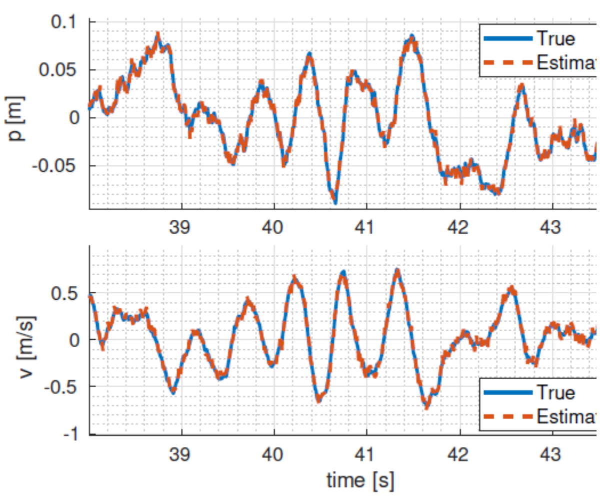
Nevertheless, the approach is effective: it is equivalent to Recursive Least Squares in linear cases or (in general) to an optimization-based method (Modified Gauss Newton [8,9], but it is implemented as a Kalman filter on parameters rather than on states.

These results are illustrative. Further refinements and a broader analysis will follow.



(a) *Parameters Reconstruction.*

Figura 3: Linear Parameters Reconstruction



(b) *State Reconstruction.*

Figura 4: Linear State Reconstruction.

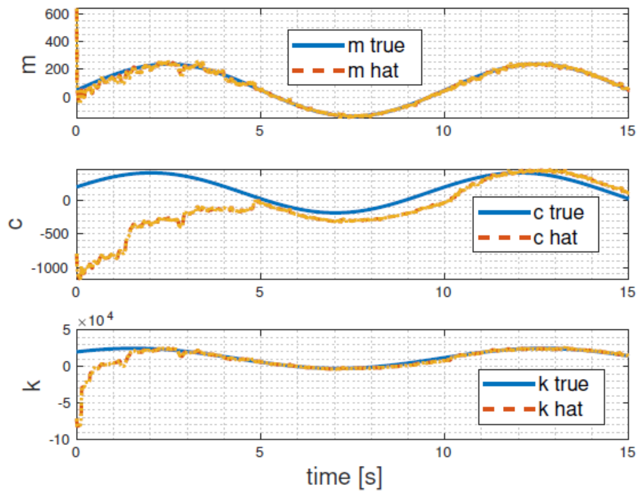


Figura 5: Nonlin Parameters Identification.

Conclusions and Future Work

The work demonstrates reconstruction over time of previously unknown pilot parameters' trajectories, from simple linear equivalents to more complex models, leveraging concise, physically consistent formulations from prior work [6] with the aim to support mitigation strategies [12] and gain better knowledge of the phenomenon. Complex, computationally demanding models can be handled by allowing time-varying components to capture unmodeled dynamics: at each instant, the simplest consistent model (e.g., mass–spring–damper harmonic oscillator) represents the system, while residual effects are absorbed by probabilistic time-adaptation of the parameter

The study is not exhaustive: limits due to process/measurement noise and parameter-rate bounds will be analyzed. Diverse parameter trajectories and increasing model mismatch will be explored and compared. The filter will be made agnostic to initial tuning by implementing methods from [11] and drawing on optimization results [8,9] also following the Linear Mean Square (LMS) approach in [12]. Upcoming work includes progressively complex tests and real-world experiments to map the method limits and define the most suitable operating range.

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