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XXXVI Cycle

Interpretable Model Learning of Quadrotor Dynamics

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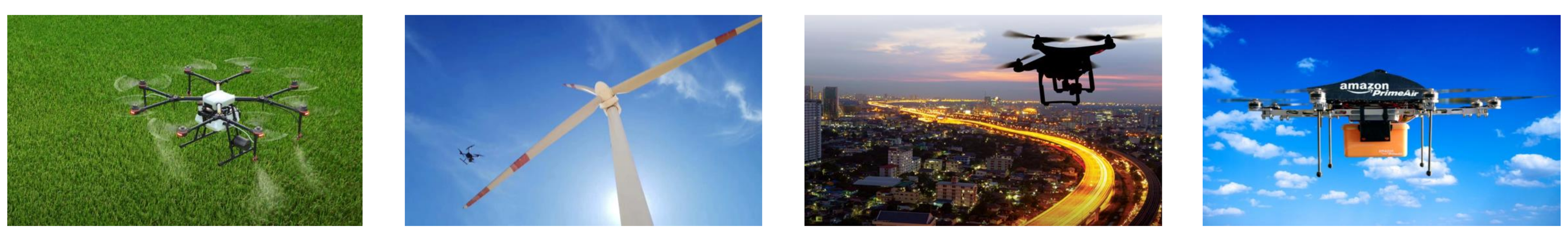
Research context and motivation

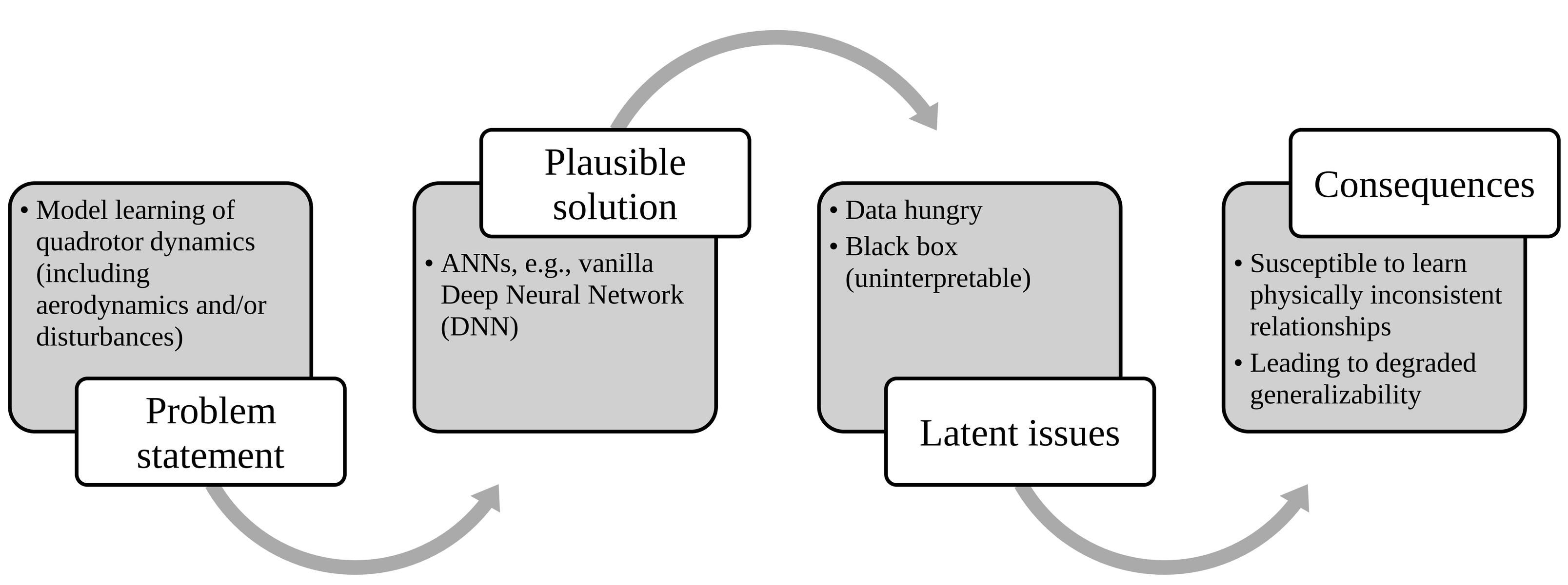
- The 21st century has witnessed an explosive growth of applications of Unmanned Aerial Vehicles (UAVs), ranging from inspection of industrial infrastructures to operations in human-interactive environments. This scenario calls for control algorithms that not only provide high tracking performance, but also enable safe and trustworthy operations, especially in populated areas, to avoid injury and property damage by all means.



- Model-based Control (MBC) techniques have found great applicability in the last decades thanks to the analytical formulation of the system dynamics. However, they rely heavily on the accuracy of the underlying model which can be significantly undermined by ubiquitous uncertainties and disturbances such as parameter uncertainties and wind gusts.
- Data-driven approaches have aroused wide attentions on learning the real system dynamics in its entire complexity from empirical data sets, in which Artificial Neural Networks (ANNs) have probably raised the most interest for UAV dynamical modeling in recent years thanks to their powerful learning capability. Nonetheless, the outcome of the learning process is typically poorly interpretable due to the black-box (a.k.a., model-agnostic) nature of ANNs, thereby leading to degraded generalizability. This issue becomes particularly harmful when ANNs are used as control-oriented model to design control actions, since such systems respond to external stimuli with behaviors that are maybe effective yet inexplicable, thus evidently reducing the overall trustworthiness of the control system.

Addressed research questions/problems

- A plausible solution of neural-network-based UAV modeling existing in the literature



- We aim to seek a learning-based approach which meets the expections of both accurate and interpretable neural modeling for quadrotor dynamics including unknown aerodynamic forces and disturbances. Such model can then be adopted as control-oriented model along with MBC techniques for controller design.

Novel contributions

- A novel neural network, namely Physics-informed Neural Network (PINN), is proposed for full dynamical quadrotor modeling, which is informed by the law of conservation of momentum during its learning phase.
- A high-fidelity simulator based on AirSim is set up to facilitate data collection with custom implementation of a parametric model of quadrotor ground effect.
- A large number of comparison and ablation studies over multiple seeds are carried out to evaluate the proposed method with conventional mathematical and purely black-box model. Covariance Confidence Ellipse (CCE) is adopted as post-hoc model interpretability technique to visualize the compliance with knowledge learned by the model.

Submitted and published works

- Weibin Gu, Stefano Primatesta, Alessandro Rizzo, "*Physics-informed neural network for quadrotor dynamical modeling*", Robotics and Autonomous Systems (under review)

Adopted methodologies

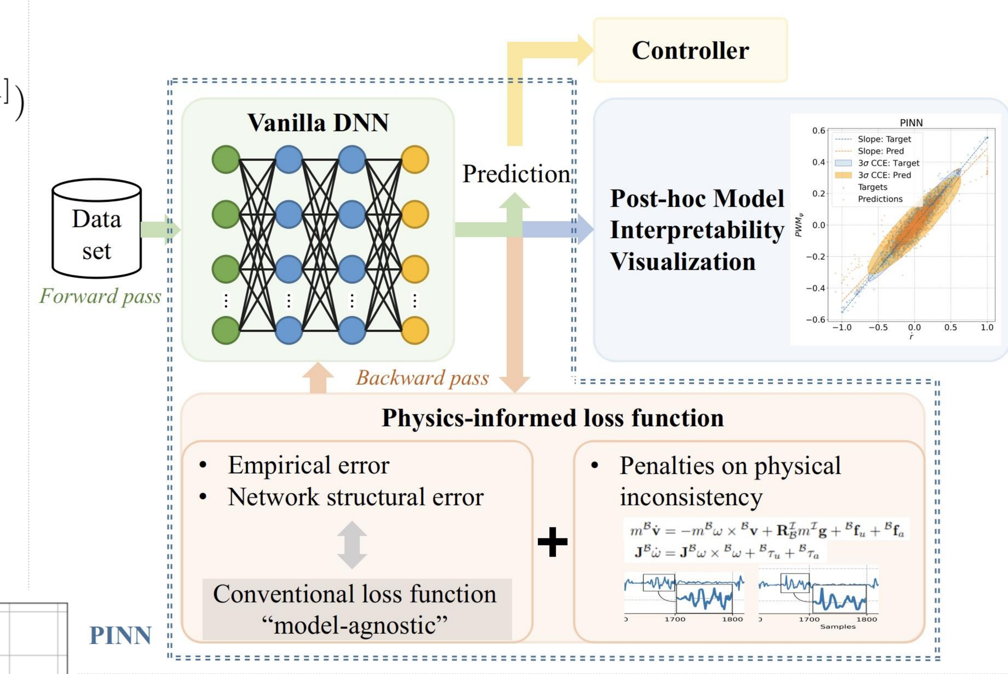
- Network structure

$$\mathrm{PINN}(X,\Theta) := f \circ \underbrace{g \circ \cdots \circ f \circ g}_{N_l \text{ hidden layers}}(\mathbf{W}^{[1]}X + \mathbf{b}^{[1]})$$

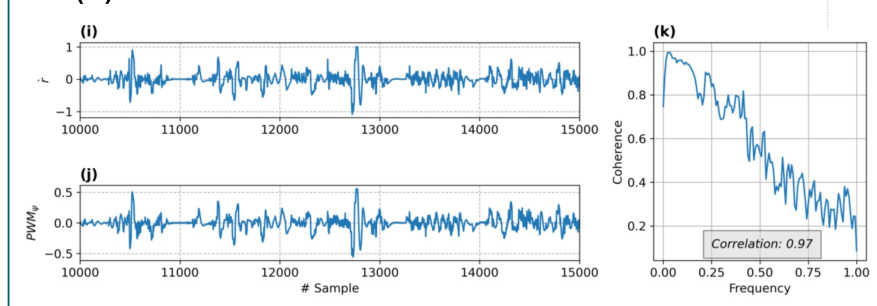
- Physics-informed loss function

(i) Conservation law of momentum

$$\mathbf{J}^{\mathcal{B}}\dot{\omega} = \mathbf{J}^{\mathcal{B}}\omega \times {}^{\mathcal{B}}\omega + {}^{\mathcal{B}}\tau_u + {}^{\mathcal{B}}\tau_a$$



(ii) Observation



Pearson Correlation Coefficient (PCC) = 0.97/0.54/0.67 for yaw/pitch/roll dynamics

⟶ Strong correlation between the derivative of angular rate and PWM signal of motors

⟶ Graphically, these data series share a similar pattern to a great extent

(iii) Embedding: local monotonicity loss

$$\mathcal{L} = \mathcal{L}_{\mathrm{MSE}} + \boxed{\sum_i \lambda^i_{\mathrm{LM}}\mathcal{L}^i_{\mathrm{LM}}} \quad i = \{\phi, \theta, \psi\}$$

Algorithm 1: Calculation of physics-informed loss function

Input: Training data $\mathcal{D}$, network parameter Θ
Parameter: Batch size N_b, hyperparameter λ_{LM}
Output: Physics-informed loss $\mathcal{L}$
Function LocalMonotonicityLoss(m, n):
  $\mathrm{LM}_m, \mathrm{LM}_n \leftarrow \tanh(m[2,N_b] - m[1,N_b-1]), \tanh(n[2,N_b] - n[1,N_b-1])$
  $\mathrm{loss} \leftarrow \frac{1}{N_b}(1 - \mathrm{LM}_m \times \mathrm{LM}_n)$ // element-wise multiplication
  return loss
$X_{batch}, Y_{batch} \leftarrow \mathrm{DataLoader}(\mathcal{D}, N_b)$ // X: features, Y: labels
$\hat{Y}_{batch} \leftarrow \mathrm{PINN}(X_{batch}, \Theta)$ // forward propagation
$\mathcal{L}_{\mathrm{MSE}} \leftarrow \frac{1}{N_b}(\hat{Y}_{batch} - Y_{batch})^2$ // (conventional) MSE
$\mathcal{L}_{\mathrm{LM}} \leftarrow \mathrm{LocalMonotonicityLoss}(\hat{Y}_{batch}, X_{batch})$ // local monotonicity loss
$\mathcal{L} \leftarrow \mathcal{L}_{\mathrm{MSE}} + \lambda_{\mathrm{LM}}\mathcal{L}_{\mathrm{LM}}$
return $\mathcal{L}$

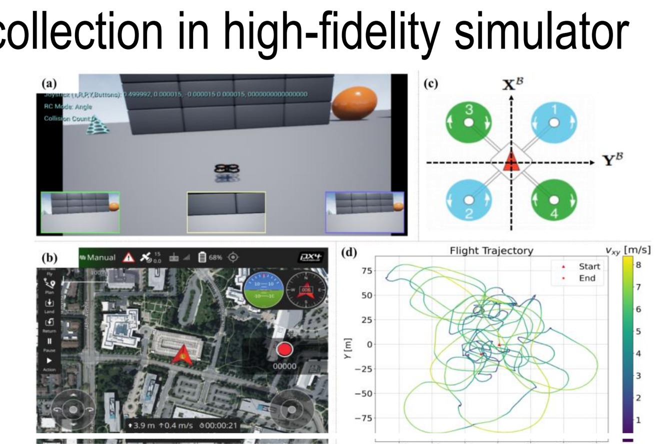
- Cyclical annealing scheduler

$$\lambda_{\mathrm{LM}} = \begin{cases} \frac{1-\beta}{1-R}\lambda_{\max} & \text{if } \beta > R \\ \lambda_{\max} & \text{if } \beta \leq R \end{cases}$$

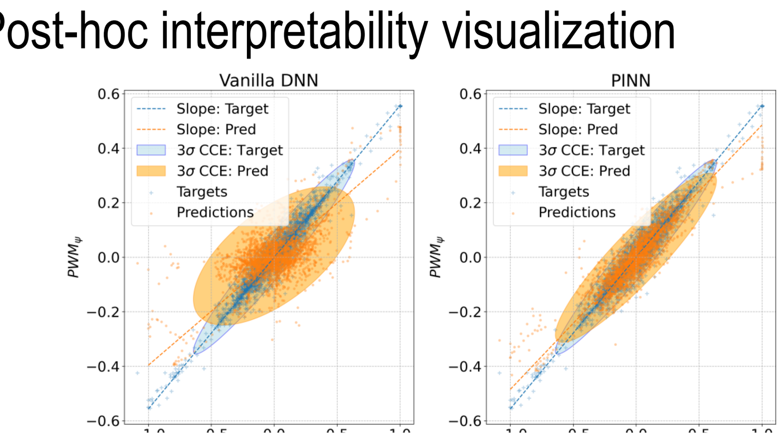
$$\beta = \frac{\mathrm{mod}\ (k, \lceil T/M \rceil)}{\lceil T/M \rceil}$$

Results

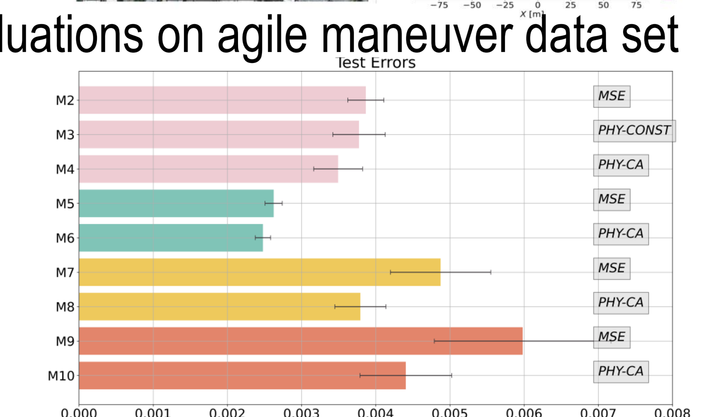
Data collection in high-fidelity simulator



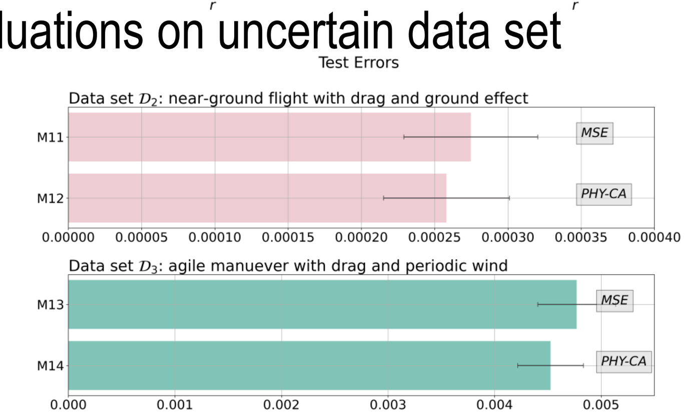
Post-hoc interpretability visualization



Evaluations on agile maneuver data set



Evaluations on uncertain data set



Future work

- To explore the potentials of PINN for online learning using real flight data
- To validate closed-loop performance by using the proposed PINN as control-oriented model in feedback linearization controller
- To investigate the combination of structured and unstructured learning

List of attended classes

- Entrepreneurial finance (08/04/2022, CFU 1)
- Project management (08/04/2022, CFU 1)
- Public speaking (08/04/2022, CFU 1)
- Data-driven model learning of dynamic systems, 5th Spring School (11/04/2022)
- Model predictive control, IMT School for Advanced Studies Lucca (01/04/2022)
- Data-driven control, University of Sannio (01/08/2022)

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