Implementation of Experience-driven Predictive Control on Computationally Constrained Platform

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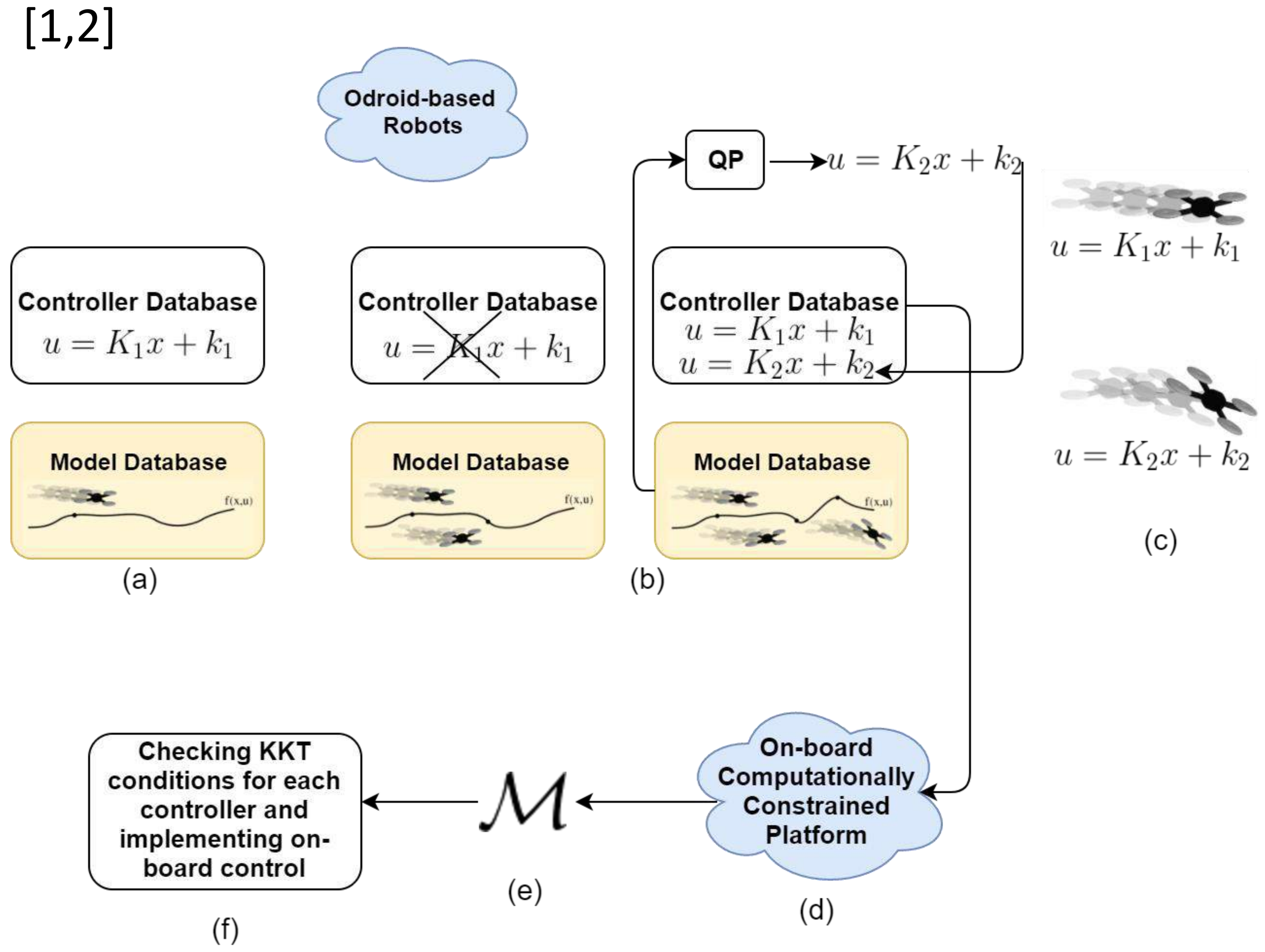
Research Objective and Challenges

Objective: Leverage past experiences to reduce the computation needed to generate new control commands in a Nonlinear Model Predictive Control (NMPC) formulation and implementing this controller on severely computationally constrained platform.

Challenges:
Evaluation on a computationally constrained platform of Pixhawk autopilot microcontroller, having 32bit STM32F427 Cortex M4 core with FPU/ 168 Mhz/256 KB RAM/2 MB Flash and 32 bit STM32F103 failsafe co-processor.

Approach

Experience-driven Predictive Control (EPC) approach that constructs online an experience database consisting of parametrized feedback controllers and dynamic models. [1,2]



(a) MAV operates away from constraint boundaries enabling it to apply a controller in database while the dynamics model continues to be updated.

(b) A new controller is added to the experience database as the MAV transitions to a more aggressive flight and the updated dynamics model predicts that the system state is approaching a constraint boundary.

(c) The MAV reuses controllers in the database based on state evolution predicted by current estimate of its dynamics model.

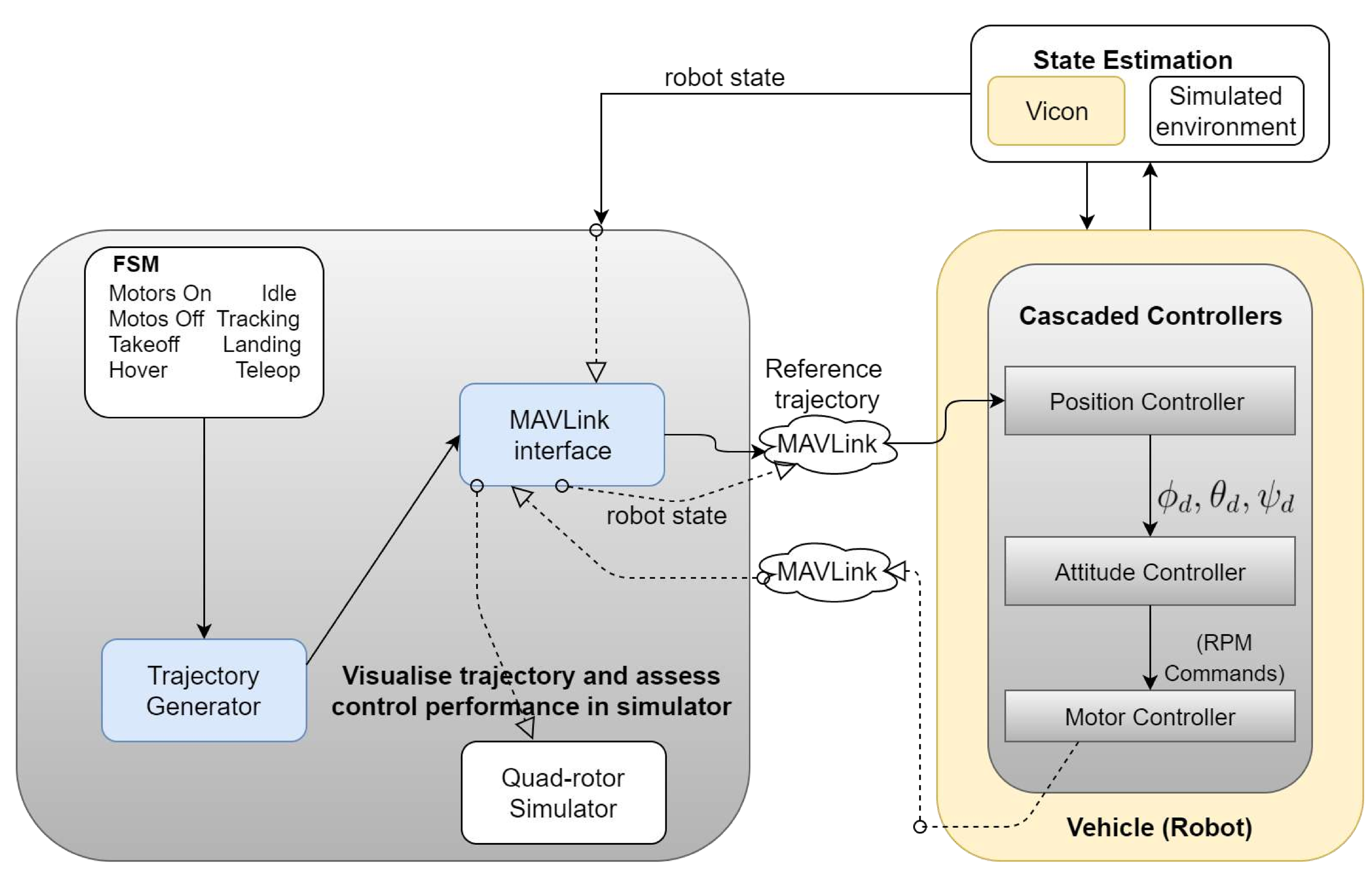
(d), (e) and **(f)**: Controller database transferred to computationally constrained platform and on-board control runs.

Experience-driven Predictive Control Algorithm

$\mathcal{M} \leftarrow \emptyset$ or $\mathcal{M}_{\text{prior}}$
while control is enabled **do**
  $\boldsymbol{x} \leftarrow$ current system state
  $\boldsymbol{r} \leftarrow$ current reference sequence
  $\mathbf{A}, \mathbf{B}, \tilde{\mathbf{c}} \leftarrow$ current dynamics model from LWPR
  for each element $m_i \in \mathcal{M}$ **do**
    Compute $\boldsymbol{u}, \boldsymbol{\lambda}$
    if $\boldsymbol{x}, \boldsymbol{r}$ satisfy parameterized KKT criteria **then**
      $\texttt{importance}_i \leftarrow$ current time, sort $\mathcal{M}$
      `solution_found` $\leftarrow$ true
      Apply affine control law $\rightarrow$ from m_i
    end if
  end for
  if `solution_found` is false **then**
  Use Existing PD Controller

u : Control Input
λ : Set of active constraints
$\mathcal{M}$: Controller Database

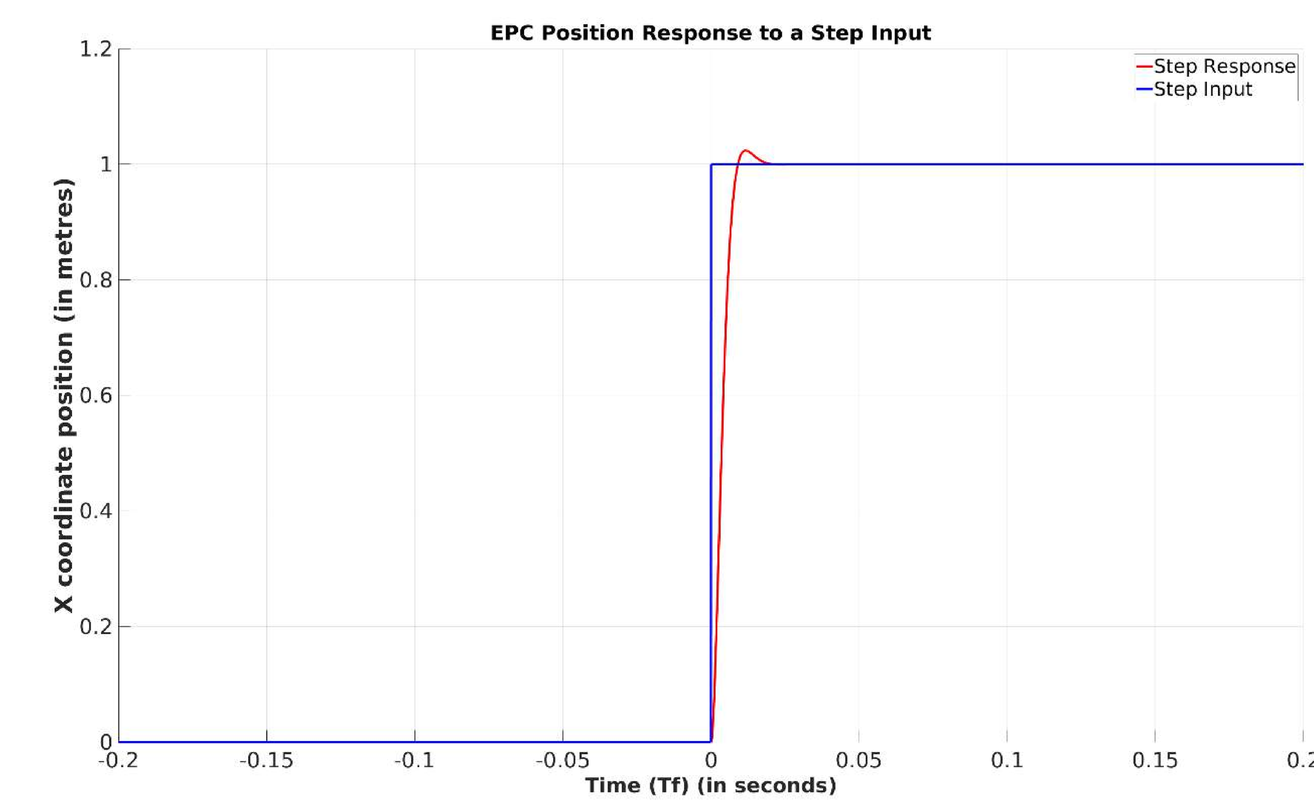
System Overview

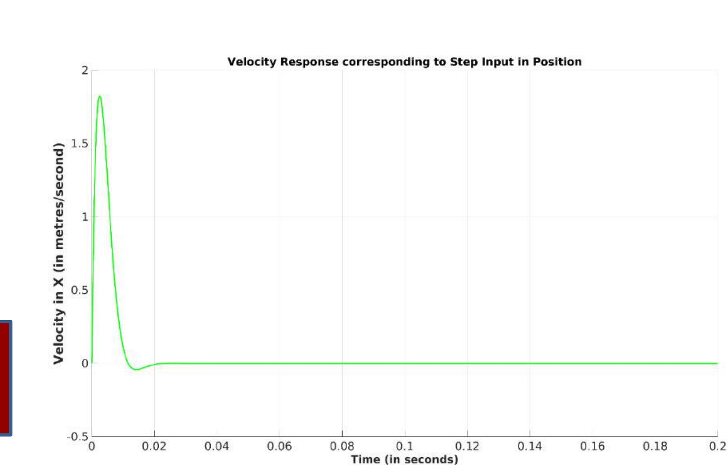


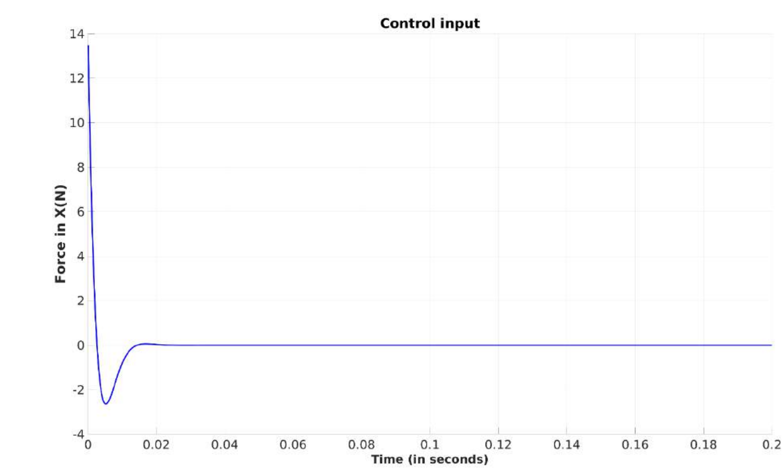
- Send the trajectory references and robot state from simulation environment to Pixhawk controller.
- Calculate final rpm commands using on-board control (PD or EPC) on computationally constrained platform (Pixhawk) and receive the rpm commands back on ground-station.
- Visualise the trajectory in simulated environment.

Preliminary Controller Performance Evaluation

- Preliminary results of EPC Controller Implementation at the embedded level for a basic desired state in a specific direction is displayed below: (Horizon Length = 10)







Conclusion and Future Work

- EPC Controller formulated on Pixhawk comprises a controller database with gains similar to PD Control. After the controller database is populated, efficient control results are leveraged via on-board control.
- Leverage Controller database generated by an external computer and extend the present formulation to Robust Experience Predictive Control using tightened constraints [2] and Markov Chain based Controller Selection [3].

References

1. V. R. Desaraju and N. Michael, "Leveraging Experience for Computationally Efficient Adaptive Nonlinear Model Predictive Control", IEEE International Conference on Robotics and Automation (ICRA), May 2017
2. V. R. Desaraju, "Safe, Efficient, and Robust Predictive Control of Constrained Nonlinear Systems", Ph.D. Thesis, Robotics Institute, Carnegie Mellon University, 2017
3. V. R. Desaraju, A. E. Spitzer, and N. Michael, "Experience-driven Predictive Control with Robust Constraint Satisfaction under Time-Varying State Uncertainty", Robotics: Science and Systems Conference (RSS), July 2017