Learning and Control of UAV Maneuvers Based on Demonstrations

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Objective

The aim is to develop an algorithm based on statistical approaches to learn any arbitrary maneuver from a given set of demonstrations.

Motivation

- ✘ For aerial vehicles, it is difficult to specify accurately how to perform a task by hand.
- ✘ Difficulties arise when considering the complexity of the aircraft's dynamics during the task design.

Approach

- State Variables:

$$s=\{\overbrace{[u,v,w]}^{Velocity};\ \overbrace{[p,q,r]}^{Angular Velocity};\ \overbrace{[\varphi,\theta,\psi]}^{Euler Angles}\}$$

- Control Variables:

$$\upsilon=[\delta E;\delta A;\delta R;\delta T]$$

- The i-th data point of the n-th demonstration:

$$\xi_i^n=\{t_i^n,s_i^n,\upsilon_i^n\}$$

- Aircraft's Dynamics[2]:

$$\dot{s}=f(s,\upsilon)$$

1 Learning

N demonstrations on the desired Trajectory

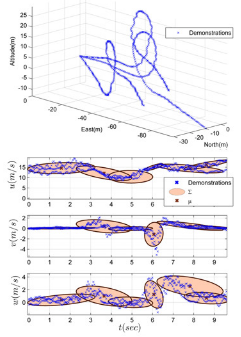
$\xi_i^1,\dots,\xi_i^N$

Using GMM to Encode the Motion $\{\pi^k,\mu^k,\Sigma^k\}_{k=1}^K$

- The model of the underlying maneuver is estimated using a ***Gaussian Mixture Model (GMM)***. Such statistical encoding of the data encodes the most relevant aspects of the training data.
- Given a GMM, each data point ξ_i^n is associated with a probability density function:

$$p(\xi_i^n)=\sum_{k=1}^K \pi_k \frac{1}{\sqrt{(2\pi)^d|\Sigma^k|}} e^{-\frac{1}{2}\left((\xi_i^n-\mu^k)^T(\Sigma^k)^{-1}(\xi_i^n-\mu^k)\right)}$$

- The GMM is trained using a standard Expectation Maximization (EM) algorithm.



$\{\pi^k,\mu^k,\Sigma^k\}$

2 Inferring the Reference Trajectory

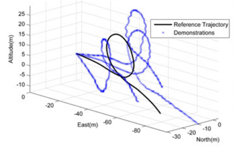
- The general form of the desired maneuver can be estimated using ***Gaussian Mixture Regression (GMR)***. Given the input variable ***t***, the output variables $[s^r;\upsilon^r]$ are:

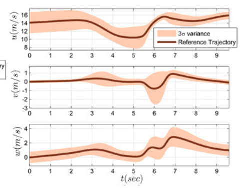
$$\begin{bmatrix} s^r \\ \upsilon^r \end{bmatrix}=\hat{\Gamma}(t)=\sum_{k=1}^K h_k(\mathbf{x})\left(\mu_o^k+\Sigma_{ot}^k(\Sigma_t^k)^{-1}(t-\mu_t^k)\right)$$

where $\mu^k=[\mu_t^k;\mu_o^k]$

$$\Sigma^k=\begin{bmatrix}\Sigma_t^k & \Sigma_{to}^k \\ \Sigma_{ot}^k & \Sigma_o^k\end{bmatrix}$$

Extracting the Statistically Optimal Trajectory $[s^r;\upsilon^r]=\hat{\Gamma}(t)$





$[s^r;\upsilon^r]$

3 Final Tuning

Correcting the extracted statistical solution based on the aircraft's dynamics $[s^r;\upsilon^r]\rightarrow[s^*;\upsilon^*]$

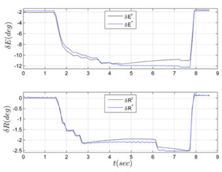
- $\dot{s}^r\neq f(s^r,\upsilon^r)\xrightarrow{Optimization}\dot{s}^*=f(s^*,\upsilon^*)$
- Optimization Problem:

$$\min_{\upsilon} J=\int_{t_0}^{t_f}\{[\upsilon(t)-\upsilon^r(t)]^T R[\upsilon(t)-\upsilon^r(t)]+\dots$$
$$+[s(t)-s^r(t)]^T Q[s(t)-s^r(t)]\}dt$$

subject to

$$\begin{cases}(1)\ \dot{s}(t)=f(s(t),\upsilon(t)) & t_0\le t\le t_f,\ s(t_0)=s^r(t_0)\\ (2)\ |\delta E|\le\delta E_{max} & (3)\ |\delta R|\le\delta R_{max}\\ (4)\ |\delta A|\le\delta A_{max} & (5)\ 0\le\delta T\le 1\end{cases}$$

- The optimization problem is solved using the Direct Sequential Method.



Results

- The performance of the algorithm was examined via 6DOF simulation for a conventional UAV for different acrobatic maneuvers. The model of each maneuver was generated from 3-5 demonstrations. Maneuvers were performed by the user on the simulator using a Joystick.
- Currently, we work on implementing the algorithm on a micro flying air vehicle in collaboration with the Laboratory of Intelligent Systems (LIS) – EPFL.

Simulation results for the loop maneuver

Footnote

[1] We would like to acknowledge the Laboratory of Intelligent Systems for providing us with the micro flying air vehicle, and Antoine Beyeler and Jean-Christophe Zufferey for piloting the aircraft.

[2] The aircraft's dynamical model can be 1) provided by the user or 2) estimated using statistical based approaches. In this work, we used the general form of the dynamics given by [2]. We are currently working on a statistical approach to learn the dynamics from a given set of data points.

Reference

[1] S. Calinon, F. Guenter and A. Billard, "On Learning, Representing and Generalizing a Task in a Humanoid Robot," IEEE transactions on systems, man and cybernetics, Part B. Special issue on robot learning by observation, demonstration and imitation, 37 (2007) 286-298.
[2] P. H. Zipfel, Modeling and Simulation of Aerospace Vehicle dynamics, AIAA education series.