On the Controllability of Agile Fixed-Wing Flight

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Introduction

Over the past few years, there have been a number of impressive demonstrations of UAV aerobatic flight (e.g. [1]). However, the maneuverability of these UAVs is no match for a human piloted aircraft, where the pilot is capable of executing extreme aerobatic maneuvers and quick recoveries in spite of turbulent airflows. We believe that maneuverable flight can be characterized by the need to maintain energy-efficient and time-dependent interactions with the surrounding airflow, a characteristic we believe can be formulated as an optimal control problem. To this end, we have begun an intensive research project in system identification, controllability analysis, and optimal control for a fixed-wing hovering aircraft (Fig 1). This abstract describes preliminary results on a practical implementation of a linear controller on a real aircraft and extensions to optimal control for a learned linear dynamic model in simulation.

Figure 1.
Autonomous Hover

Stabilizing a Hovering UAV

We have begun with an investigation into the controllability of our plane in a Vicon MX motion capture environment during vertical hover. The motion capture environment provides real-time sub-millimeter tracking of the plane along with its control surface deflections and has provided a convenient and non-obtrusive way of collecting flight data for system identification. Our initial task was to regulate the orientation of the aircraft to a vertical hovering state. Orientation control is trivial, and can be regulated through simple P.D. control on the orientation error.

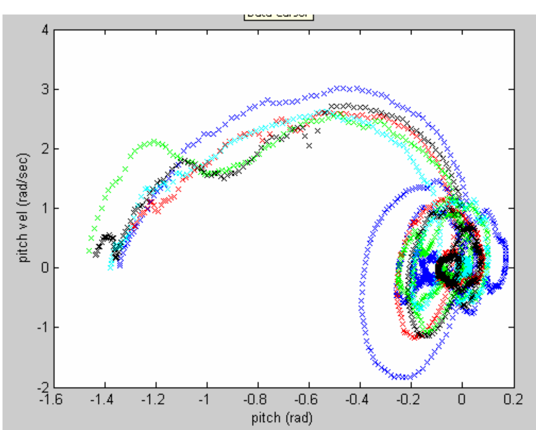

Figure 1.
Samples of pitch basin of attraction

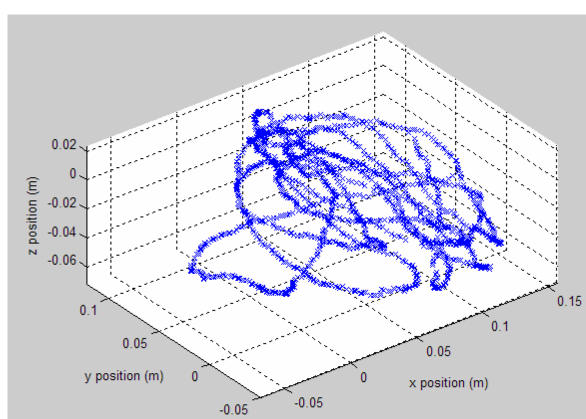

Figure 2.
P.D. control position trajectory

We were interested in testing the basin of attraction of this simple controller and performed a few trials of the plane starting from horizontal (i.e. normal flight orientation) and were surprised to find the robustness of this simple controller away from the linearization point. Fig. 1 shows five samples of the basin of attraction (for pitch) starting from horizontal. However, as shown in Fig. 2, the noisy environment in combination with suboptimal gains makes the plane drift away from its initial state in (x,y) coordinates. The regulation of these state variables becomes non-trivial due to the fact that we are completely underactuated in these degrees of freedom. Our goal is then to learn a dynamic model of the plane such that we can control all state variables using linear optimal control.

Controllability Analysis and Optimal Control

Since we are simultaneously trying to regulate orientation as well as absolute position, the task becomes non-trivial. Namely, for a given desired orientation and position (e.g. in an aerobatic maneuver), the required control surface deflections will differ and will depend on the aircraft's control derivatives. We fit a linear state-space model of our aircraft by logging motion capture data of the orientations, positions, and control surface deflections (Fig. 3). Using the learned model, we computed an optimal linear controller for the regulation task (LQR). The task was to regulate all states to zero from an arbitrarily chosen state (x=1,y=1,z=1, roll=.1,pitch=.1,yaw=.1 ; units in meters and radians).

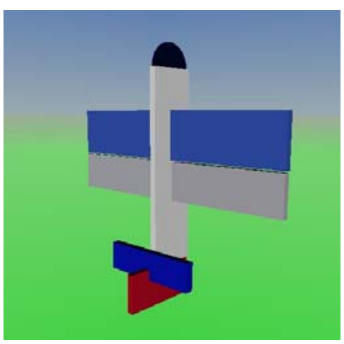

Figure 3.
Simulator using learned dynamics

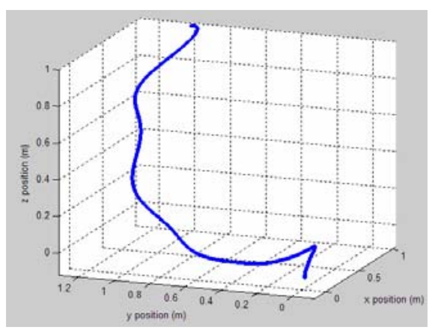

Figure 4.
LQR position trajectory

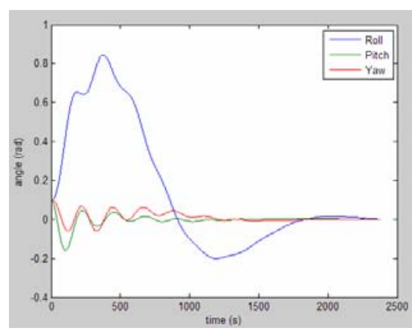

Figure 5.
LQR orientation trajectory

Fig. 4 shows the position path and Fig. 5 shows the Euler angle orientation trajectories. Currently, we are performing statistical test for error bounding our dynamic model. A controllability analysis on our currently learned model shows that it is full-state controllable. Once this analysis is complete and we are confident in our model, we will transfer our control system to the real plane.

References

[1] Pieter Abbeel, Varun Ganapathi, and Andrew Y. Ng. Learning vehicular dynamics, with application to modeling helicopters. NIPS, 2006.

[2] William E. Green and Paul Y. Oh. Autonomous Hovering of a Fixed-Wing Micro Air Vehicle. IEEE International Conference of Robotics and Automation (ICRA). 2006.