Optimizing Reference Commands for Concurrent Learning Adaptive-Optimal Control of Uncertain Dynamical Systems

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Optimal control of autonomous aircraft with modeling uncertainties is a challenging problem, especially considering that onboard computational resources may be limited. A concurrent learning direct model reference adaptive control architecture with reference command optimization is presented. Exponential parameter convergence properties of concurrent learning adaptive controllers make an uncertain system behave like a preselected linear reference model. The reference signal is shaped optimally by using a linear Model Predictive Control approach. Since the reference model is preselected, optimal solutions for certain flight conditions can be generated a-priori, such that the optimal control problem does not need to be solved online. Stability of the overall architecture is analyzed using a Lyapunov framework. Numerical simulations are presented, showing increased controller performance and the abidance of input and state constraints.

I. Introduction

Model Reference Adaptive Control (MRAC) for uncertain dynamical systems is a well studied topic in adaptive control. The aim of MRAC is to make a closed loop system behave like a-priori chosen reference dynamics. This goal is achieved by adjusting adaptive parameters online based on the minimization of a quadratic cost.The underlying assumption is that there exists an optimal set of gains which achieves this goal. If the adaptive gains do converge to their true values the closed loop system matches the reference dynamics. In most classic[1–4] and some recent[5,6] MRAC approaches only instantaneously available data is used to update the adaptive parameters. In this case the parameters only converge to their true values if the regressor vector is persistently exciting.[4,7] Ensuring persistency of excitation is often not feasible, especially if the functions in the regressor vector are nonlinear. Furthermore, enforcing excitation leads to a waste of fuel, puts additional stress on the aircraft and might be operationally undesirable.

Chowdhary introduced a method, called concurrent learning, where instantaneous data is used concurrently with specifically stored data in order to update the adaptive parameters.[8,9] The underlying idea is that if the data points are stored at a time when the regressor vector was excited, this information can be used in future updates to achieve parameter convergence. A verifiable condition on the linear independence of the stored data is enough to guarantee parameter convergence. Furthermore, Chowdhardy showed that concurrent learning leads to exponential tracking and parameter convergence if the uncertainty can be linearly parametrized.[8,9]

However, even if the closed loop system matches the reference dynamics, the plant might still perform worse than what is actually physically possible. Optimal control methods aim to leverage the full capabilities of the plant while simultaneously ensuring that constraints on inputs and states are not violated. A heavely studied technique for linear and nonlinear systems with constraints is Model Predictive Control[10–12] (MPC). The main limitation of MPC is its requirement of high computational power which needs to be available onboard the controlled vehicle. Hoewever, in the past it was shown that for constrained linear systems most of the computation can be moved offline,[13–19] thus reducing the online compuation to a table-lookup or the evaluation of an analytical function, which yields the optimal control law. Such techniques have been implemented for example for the attitude control of a micro-satellite.[20] In the past, MPC also has been applied successfully together with concurrent learning adaptive controllers using a switched system architecture based on a criterion on the quality of the uncertainty approximation.[21,22]

Shaping various signals to improve certain performance characteristics has attracted increasing interest in recent years. Shaping the reference command in an optimal sense has become known as the reference governor.[23–27] The

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main goal of this approach is to enforce constraints on closed-loop system outputs and control variables. Hoewever, often the plants are considered to be linear and/or a controller already exists which stabilizes the system. Furthermore, the approaches mentioned before often require the solution of an optimal control problem onboard the vehicle, thus requiring a high amount of computational power. An approach where this is not the case can be found in Ref. 28. In Ref. 29 an adaptive error governor is introduced. Here, the error between reference command and state is used in order to modify the adaptive law. In Ref. 30 a command governor approach is presented which aims on increasing the transient performance of a model reference adaptive controller.

In this paper we propose a non-switching concurrent learning adaptive-optimal controller where the exogenous reference commands are shaped based on an a-priori determined optimal solution of a chosen linear reference model. One of the main challenges in implementing MPC, and specifically the architectures in[21,22] is to guarantee the feasibility of obtaining an optimal solution online on resource constrained aircraft. In this paper, this problem is tackled by solving offline the optimal control problem for the linear reference model in a predescribed parameter space.[13–19] This becomes possible, since the concurrent learning adaptive controller is able to render the closed loop dynamics equal to the reference model. For numerical simulation a lookup table is used to compute the optimal control law online. We show that by shaping the reference command, the performance of the controller is significantly increased while given input and state constraints are not violated and, through the concurrent learning adaptive controller, stability of the closed loop system is preserved.

The novelty of the proposed approach lies in the fact that it combines several properties of the above-mentioned signal shaping methods. In particular, the plant can be nonlinear, as long as the system uncertainties are matched and enough control authority is available in order for the adaptive controller to render the closed loop system equal to the reference model. But most importantly, the optimal solution of the reference command shaping can be moved offline, since the reference model dynamics are selected a-priori.

Figure 1 shows the proposed structure of the controller. In general the architecture consists of two parts. First, the exogenous reference command is shaped such that the linear reference model is controlled optimally, simultaneously abiding chosen input and state constraints. Therefore, the current state of the system and the available control authority serve as inputs to the reference command shaping. Secondly, the control architecture consists of a concurrent learning adaptive controller which aims to make the closed loop dynamics behave like that of the chosen reference model. Hence, if the adaptive parameters do converge and the reference model is controlled optimally, then the plant is controlled optimally too. Note, that for reference command shaping only the difference between the physically available control authority and the one needed by the adaptive controller is used. This way, it is ensured that the concurrent learning adaptive controller can still drive the closed loop dynamics close to that of the reference model dynamics.

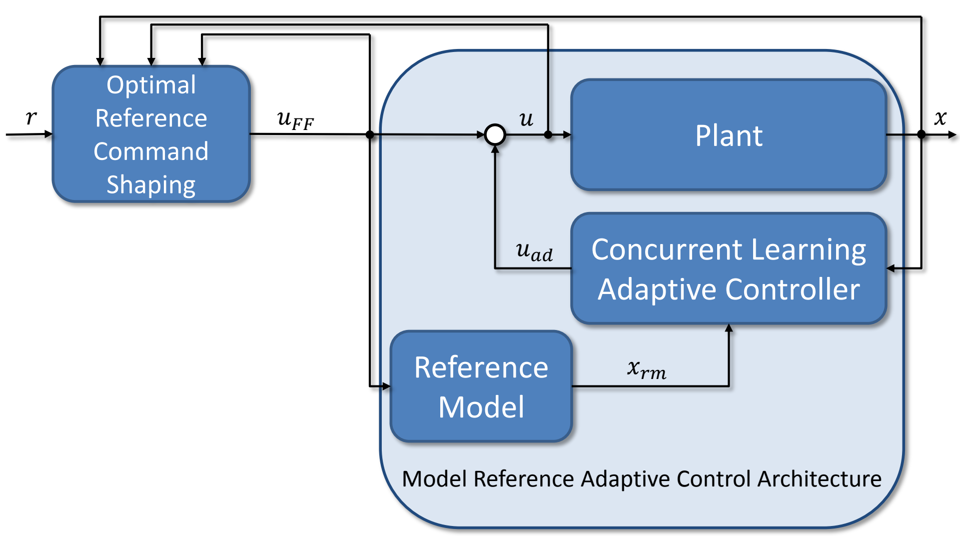

Figure 1. Control Architecture for proposed framework.

Preliminary simulation results using the proposed control architecture as described in Figure 1 are presented. The linearized longitudinal dynamics of an agile fighter aircraft serve as the plant. The aim of the concurrent learning adaptive controller is to let the closed loop system behave like an a-priori chosen linear reference model. The reference commands are shaped such that the reference model abides input and state constraints, while leveraging the full capabilities of the plant. In particular, the pitch rate is constrained from above and below by $\pm 60°/s$. The reference command for the angle of attack consists of two parts. First, a sine with amplitude of $5°$ and a frequency of $2rad/s$ is commanded for 3 seconds. With this, enough excitation is induced in the system, which again allows the concurrent learning adaptive controller to store enough linearly independent data points, in order to achieve parameter and tracking error convergence. After 3 seconds consecutive step inputs, each lasting 7.5 seconds with an amplitude of $10°$, are commanded.

Figure 2 shows the results of the numerical simulations. The proposed control architecture is compared against a concurrent learning adaptive controller without reference command shaping. The latter was shown to achieve exponential tracking and parameter error convergence if a condition on linearly independence of the stored data is met.[8,9] In this case the closed loop system behaves like the a-priori chosen reference model. If, in addition, the reference command is shaped based on the a-priori determined optimal solution of the linear reference model, the performance is seen to improve drastically. This is due to the fact that the full control authority is used in order to control the plant. Simultaneously, the constraint, which is placed on the pitch rate, is not violated.

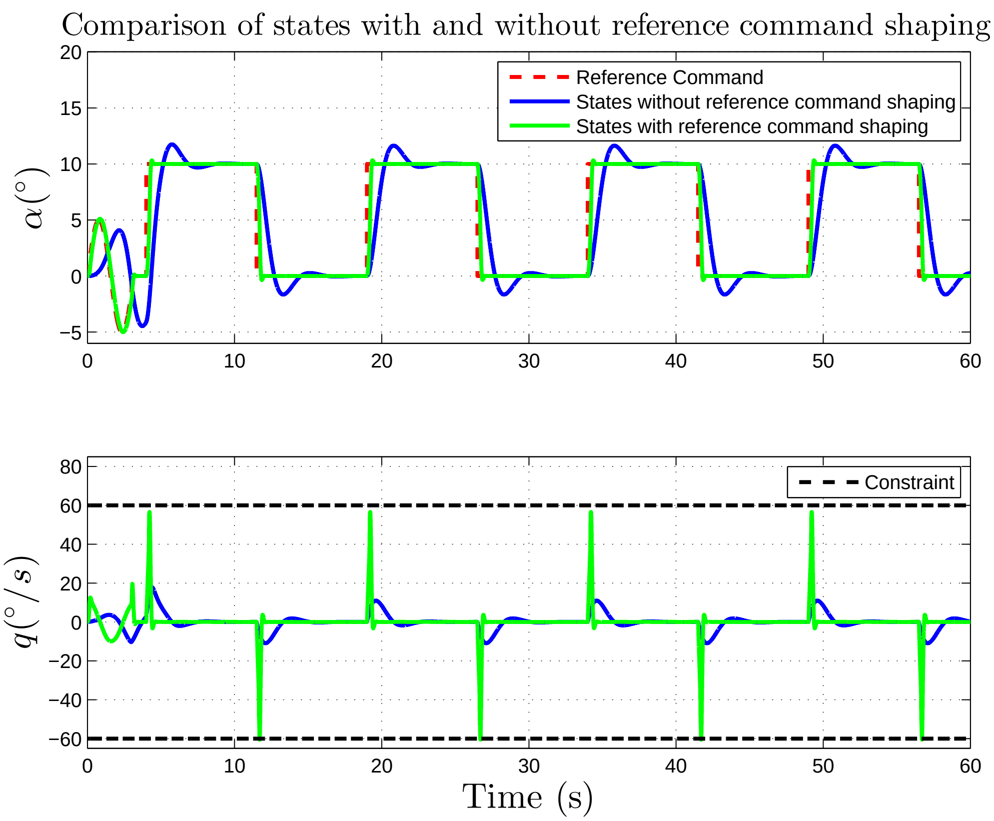

Figure 2. Comparison of states with and without reference command shaping. It can be seen that the performance increases drastically if the reference command is shaped such that the linear reference model is controlled optimally. Simultaneously the constraint on the pitch rate is abided.

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