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Chapter 1 : Model predictive control - Wikipedia

The Receding Horizon Control Principle The above two problems are addressed by the idea of receding horizonoptimisation. This idea can be summarised as follows.

This poses challenges for both NMPC stability theory and numerical solution. This allows to initialize the Newton-type solution procedure efficiently by a suitably shifted guess from the previously computed optimal solution, saving considerable amounts of computation time. The similarity of subsequent problems is even further exploited by path following algorithms or "real-time iterations" that never attempt to iterate any optimization problem to convergence, but instead only take a few iterations towards the solution of the most current NMPC problem, before proceeding to the next one, which is suitably initialized; see, e. While NMPC applications have in the past been mostly used in the process and chemical industries with comparatively slow sampling rates, NMPC is being increasingly applied, with advancements in controller hardware and computational algorithms, e. Explicit MPC is based on the parametric programming technique, where the solution to the MPC control problem formulated as optimization problem is pre-computed offline [13]. This offline solution, i. Every region turns out to geometrically be a convex polytope for linear MPC, commonly parameterized by coefficients for its faces, requiring quantization accuracy analysis [14]. Obtaining the optimal control action is then reduced to first determining the region containing the current state and second a mere evaluation of PWA using the PWA coefficients stored for all regions. If the total number of the regions is small, the implementation of the eMPC does not require significant computational resources compared to the online MPC and is uniquely suited to control systems with fast dynamics [15]. A serious drawback of eMPC is exponential growth of the total number of the control regions with respect to some key parameters of the controlled system, e. There are three main approaches to robust MPC: In this formulation, the optimization is performed with respect to all possible evolutions of the disturbance. Here the state constraints are enlarged by a given margin so that a trajectory can be guaranteed to be found under any evolution of disturbance. This uses an independent nominal model of the system, and uses a feedback controller to ensure the actual state converges to the nominal state. This uses a scenario-tree formulation by approximating the uncertainty space with a set of samples and the approach is non-conservative because it takes into account that the measurement information is available at every time stages in the prediction and the decisions at every stage can be different and can act as recourse to counteract the effects of uncertainties. The drawback of the approach however is that the size of the problem grows exponentially with the number of uncertainties and the prediction horizon. A survey of commercially available packages has been provided by S. Badgwell in Control Engineering Practice 11 â€" Therefore, MPC typically solves the optimization problem in smaller time windows than the whole horizon and hence may obtain a suboptimal solution. However because MPC makes no assumptions about linearity, it can handle hard constraints as well as migration of a nonlinear system away from its linearized operating point, both of which are downsides of LQR.

Chapter 2 : Receding horizon control Research Papers - calendrierdelascience.com

Receding Horizon Control (RHC) introduces the essentials of a successful feedback strategy that has emerged in many industrial fields. RHC has several advantages over other types of control: greater adaptability to parametric changes than infinite horizon control; better tracking than PID and good.

Linear Model Predictive Control Introduction Model Predictive Control MPC is a modern control strategy known for its capacity to provide optimized responses while accounting for state and input constraints of the system. This introduction only provides a glimpse of what MPC is and can do. In fact, MPC is a solid and large research field on its own. In the core idea of MPC is the fact that a model of the dynamic system the vehicle in our case is used to predict the future evolution of the state trajectories in order to optimize the control signal and account for possible violation of the state trajectories while bounding the input to the admissible set of values. The concept is shown in Figure 1. The basic concept of model predictive control as a model-based and optimization-based solution. Receding Horizon Strategies Model Predictive Control relies on the concept of receding horizon optimal control derivation. According to this approach, at time t we solve to find the optimal control sequence over a finite future horizon of N steps. The relevant formulation is shown below: Essentially, we exploit feedback to update the optimization over the time horizon selected to predict the future evolution of the system outputs. To understand the concept of receding horizon control, one can consider the analogy of a driver steering a car see Figure 2. Prediction model is what describes how the vehicle is expected to move on the map. Set point is the desired location. Cost Function may be the goal of minimum time, minimum distance etc. The receding horizon control strategy would re-plan the route of the car and the corresponding driver actions periodically in time, find the overall set of actions over a time horizon, apply the first and then re-plan for the next-step. Car driving requires predictive thinking and optimal control derivation. Image screenshot from "Stunt Rally". In fact, the model selection has a major role regarding the computational complexity of the algorithm, its theoretical properties e. At the same time, the selected objective and imposed constraints also influence and define these properties. A good model for MPC is a model that is descriptive enough, captures the dominant and important dynamics of the system but also remains simple enough such that it allows the optimization problem to be tractable and solvable in real-time. Finding a good balance between these two requirements is a balance. A good model is simple as possible, but not simpler. Therefore, the following questions should be answered before deriving a model to be used with Model Predictive Control methods: What is the required -for control purposes- order of the system? Can we decouple the system? What assumptions are required? Design and Implementation of a Linear MPC Design, implementation and efficient execution of model predictive control is a very challenging problem that requires deep understanding of optimization methods and strong coding skills. However, the great success of the method lead to the fact that one can use advanced software tools to achieve this goal quite seamlessly. Although deep understanding is always beneficial, implementation of a single MPC may be nothing more than writing a very brief abstract program. Code Generation for Convex Optimization ". CVXGEN generates fast custom code for small, QP-representable convex optimization problems, using an online interface with no software installation. With minimal effort, turn a mathematical problem description into a high speed solve. As can be found in the relevant example " Example: B n,m transfer matrix. Q n,n psd state cost. R m,m psd input cost. S nonnegative slew rate limit. T maximum input box constraint. T-1 slew rate constraint. Proudly powered by Weebly.

Chapter 3 : Linear Model Predictive Control - Dr. Kostas Alexis

Receding horizon control (RHC), also known as model predictive control (MPC), is a general purpose control scheme that involves repeatedly solving a constrained optimization problem, using predictions of future costs, disturbances, and constraints over a moving time horizon to choose the control action.

This is an open access article distributed under the Creative Commons Attribution License , which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. A new cost function for a finite horizon dynamic game problem is first introduced, which includes two terminal weighting terms parameterized by a positive definite matrix, called a terminal weighing matrix. Secondly, the RHHC is obtained from the solution to the finite dynamic game problem. Thirdly, we propose an LMI condition under which the saddle point value satisfies the nonincreasing monotonicity. Finally, we show the asymptotic stability and boundedness of the closed-loop system controlled by the proposed RHHC. The proposed RHHC has a guaranteed performance bound for nonzero external disturbances and the quadratic cost can be improved by adjusting the prediction horizon length for nonzero initial condition and zero disturbance, which is not the case for existing memoryless state-feedback controllers. It is shown through a numerical example that the proposed RHHC is stabilizing and satisfies the infinite horizon performance bound. Furthermore, the performance in terms of the quadratic cost is shown to be improved by adjusting the prediction horizon length when there exists no external disturbance with nonzero initial condition. Chemical processing systems, transportation systems, communication systems, and power systems are typical examples of time-delay systems. As one of time-delay systems, an input-delayed system is common and preferred for easy modeling and tractable analysis. Much research on input-delayed systems has been made for decades in order to compensate for the deterioration of the performance due to the presence of input delay [1 â€” 5]. The RHC for ordinary systems has been extended to problem in order to combine the practical advantage of the RHC with the robustness of the control [9 â€” 11]. This work investigated the nonincreasing monotonicity of the saddle point value corresponding to the optimal cost in LQ problems. For time-delay systems, there are several results for the RHC [12 â€” 15]. A simple receding horizon control with a special cost function was proposed for state-delayed systems by using a reduction method [12]. However, it does not guarantee closed-loop stability by design, and therefore stability can be checked only after the controller has been designed. The general cost-based RHC for state-delayed systems was introduced in [13]. This method has both state and input weighting terms in the cost function. Furthermore, it has guaranteed closed-loop stability by design. The RHC in [13] is more effective in terms of a cost function since it has a more general form compared with memoryless state-feedback controllers. Although the stability and performance boundedness were shown in [14], the advantage of RHHC over the memoryless state-feedback controller was not mentioned there. While the results mentioned above deal with state-delay systems, the results given in [15] deal with the RHC for input-delayed systems. It extends the idea in [13] to input-delayed systems. However, to the best of our knowledge, there exists no result on the receding horizon control for input-delayed systems. The purpose of this paper is to lay the cornerstone for the theory on RHHC for input-delayed systems. The issues such as solution, stability, existence condition, and performance boundedness will be addressed in the main results. Furthermore, the advantage of RHHC for input-delayed systems over the memoryless state-feedback controller will be illustrated by adjusting the prediction horizon length. The rest of this paper is structured as follows. In Section 2 , we obtain a solution to the receding horizon control problem. In Section 3 , we derive an LMI condition, under which the nonincreasing monotonicity of a saddle point value holds. In Section 4 , we show that the proposed RHHC has asymptotic stability and satisfies performance boundedness. In Section 5 , a numerical example is given to illustrate that the proposed RHHC is stabilizing as well as guarantees the performance bound. Finally, the conclusion is drawn in Section 6. Throughout the paper, the notation implies that the matrix is symmetric and positive definite positive semi-definite. Similarly, implies that the matrix is symmetric and negative definite negative semidefinite.

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Chapter 4 : Receding Horizon Covariance Control

Model predictive control (MPC) is an advanced method of process control that is used to control a process while satisfying a set of constraints. It has been in use in the process industries in chemical plants and oil refineries since the s.

Project This set of lectures builds on the previous three weeks and explores the use of online optimization as a tool for control of nonlinear control. We being with an high-level discussion of optimization-based control, refining some of the concepts initially introduced in Week 1. We then describe the technique of receding horizon control RHC , including a proof of stability for a particular form of receding horizon control that makes use of a control Lyapunov function as a terminal cost. A detailed implementation example, the Caltech ducted fan, is used to explore some of the computational tradeoffs in optimization-based control. Students should be familiar with the concepts of trajectory generation and optimal control as described in Weeks For the proof of stability for the receding horizon controller that we use, familiarity with Lyapunov stability analysis at the level given in AM08, Chapter 4 Dynamic Behavior is required. In lecture, I will use the textbook notation. HW 4 due 6 Feb Students working on the course project should do problems 3. References and Further Reading R. Information Technology for Dynamical Systems, T. Constrained model predictive control: Stability and optimality , D. This is one of the most referenced comprehensive survey papers on MPC. Gives a nice overview about its history and explains the most important issues and various approaches. Frequently Asked Questions Q: How do you do trajectory optimization using differential flatness The basic idea in using flatness for optimal trajectory generation is to rewrite the cost function and constraints in terms of the flat outputs and then parameterize the flat outputs in terms of a set of basis functions: This process is described in a more detail in the lectures notes Section 4. I was a bit sloppy defining CLFs in lecture. The formal definition is given in the lectures notes Section 2.

Chapter 5 : CDS b: Receding Horizon Control - MurrayWiki

Abstract. We propose the receding horizon control (RHHC) for input-delayed systems. A new cost function for a finite horizon dynamic game problem is first introduced, which includes two terminal weighting terms parameterized by a positive definite matrix, called a terminal weighing matrix.

Chapter 6 : Receding Horizon Control for Input-Delayed Systems

This theory, however, does not extend to control of the transient uncertainties and to date there exist no practical engineering solutions to the problem of directly and optimally controlling the uncertainty in a linear system from one Gaussian distribution to another.