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Distributed and Robust Control Strategies for Nonlinear Fleet Coordination

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Résumé (800 mots maxi) :

In today's operating landscape, systems are becoming more and more complex and large, and therefore it is necessary to analyze them as Systems of Systems (SoS) [1].
In a nutshell, an SoS is a finite number of agents that communicate with each other and compute local optimal controls to achieve a common goal. This approach has been used in different applications (such as healthcare, transportation, and government agencies), showing an enhancement in efficiency, resilience, and sustainability. Therefore, it is crucial to propose novel distributed and robust control techniques for this class of complex systems.
In distributed control systems, the control action is shared among a finite number of local controllers that communicate with each other.
The term "robust control" refers instead to all the control techniques dealing with the problem of designing accurate control systems in the presence of significant uncertainties.
While distributed robust control theory for linear systems is well-established [2-7], it remains an active area of research when extended to nonlinear systems. When addressing nonlinearities, as always, two primary approaches are available: either utilize tools specifically designed for nonlinear systems or approximate and linearize the system to apply established linear control methods. Hence, both possibilities have been considered and validated.

Let us consider first the case where nonlinearities are not approximated. Outlining a state-of-the-art, it turns out that an emergent control technique is Model Predictive Control (MPC) [8]. It is an advanced feedback optimal control technique that uses an internal model to predict the future behavior of the plant over a future prediction horizon. Then, the control action is obtained by solving an optimization problem that minimizes a cost function (usually penalizing both the tracking errors and the control itself) subject to some constraints. Due to its simplicity and intuitive approach, MPC, initially introduced for chemical production processes, has been adopted in various fields. Different variations with distinct optimization problem definitions have also been proposed in the literature. One possibility is to use a nonlinear model in the definition of the MPC problem, which consequently becomes an NLP problem. Nonlinear MPC (NMPC) can deal with nonlinearities and actuator bounds elegantly but at a high computational cost.
Hence, as a case study of application, a distributed NMPC scheme has been proposed for a heterogeneous fleet composed of a steering car and a quadcopter. Since the two robots were communicating, an NMPC controller was defined for each agent to follow a reference trajectory (in the case of the car, obstacle avoidance was considered by adding some inequality constraints). Then, the ground vehicle, in the role of the leader, communicates its one-step future position to the drone. The drone then uses this information as a reference. Various simulations were conducted in MATLAB/Simulink, altering the reference trajectories, the number of obstacles, and their positions. Results show that the ground car can avoid detected obstacles, keeping the tracking errors of both robots on the order of a few centimeters. For more details, check the paper [9].

The second approach is to transform the nonlinear model, either algebraically or by approximation, into a linear one to apply all the results developed for this second class. Among the various proposed techniques, one is feedback linearization. As a case study, the fleet formation problem for a homogeneous group of unicycle-like robots is considered. The idea is to propose an efficient control law that is robust to disturbances and ensures collision avoidance.
Although the unicycle dynamics are nonlinear, if the control objective is shifted from the center of rotation to a point located at a predefined distance from it, the resulting (x, y)-dynamics become linear. Therefore, the entire fleet dynamics can be expressed as a linear continuous-time system, which can then be discretized using the Euler method.
Once the discrete-time state equations are obtained, the two main goals can be addressed.
In particular, the first objective is to propose a control law that stabilizes the system under the worst-case scenario and such that for each robot, the controller only uses local information. This control problem can be defined as a soft-constrained linear-quadratic dynamic game over a one-step horizon, as in [10]. In the paper, the authors prove that the linear policy is optimal and the optimal gains can be obtained by solving an LMI.
To attain the second point, a hierarchy is defined between agents, and artificial potential fields are used. The repulsive forces are then added to the optimal linear strategy so that the agents can correct their trajectories.
Again, MATLAB/Simulink simulations were conducted considering different final configurations, both in terms of formation shape and final velocity (whether stationary or in motion). In all scenarios, the formation was achieved in less than 20 seconds without any collisions.

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