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Application of distributed predictive control to motion and coordination problems for unicycle autonomous robots

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HIGHLIGHTS

- DPC control is tailored to address dynamically decoupled systems.
- Linear inequalities are used for obstacle and collision avoidance constraints.
- Motion and coordination problems are addressed by formulating optimization problems.
- Design and implementation issues for control of unicycle robots are addressed.
- Real and simulation tests are illustrated.

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ABSTRACT

This paper presents a Distributed Predictive Control (DPC) approach for the solution of a number of motion and coordination problems for autonomous robots. The proposed scheme is characterized by a multilayer structure: at the higher layer the reference trajectories of the robots are computed as the solution of suitable optimization problems. It is shown that, at this level, the definition of the cost function to be minimized allows to consider many different problems, such as formation control, coverage and optimal sensing, containment control, inter-robot and obstacle collision avoidance, and patrolling in an unknown environment. At the lower layers of the control structure, proper state and control reference trajectories are defined and a robust Model Predictive Control (MPC) problem is solved by each robot. To reduce the computational burden required by the algorithm, collision and obstacle avoidance constraints are reformulated in linear terms, so that the optimization problem to be solved on-line is a Quadratic Programming (QP) one. A number of experimental and simulation results are reported to witness the flexibility and performances of the method.

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1. Introduction

The development of algorithms for the distributed coordination and control of large scale interconnected or independent systems has received a great attention in recent years see, e.g., [1–6]. These problems are of particular interest in the robotic field, motivated by the widespread diffusion of autonomous robotic systems, which require efficient distributed control strategies for motion, coordination, and cooperation, see [7–9] and the references therein. Among the main problems of interest, it is possible to recall formation control, coverage and containment for sensing, obstacle and inter-robot collision avoidance, and border patrolling.

Distributed coordination includes a number of fundamental issues, such as *flocking* [8], *formation tracking and control* [9]. Formations can be represented in many ways, for example by means of *virtual structures* [10,11], using a *leader–follower* representation [12], or through the so-called *formation constraint function* [13]. These problems, including *obstacle and inter-robot collision avoidance*, are tackled with *potential functions*, *gradient methods* [14], linear feedback control laws [15], and *consensus* [16]. Other well-studied coordination control problems include *containment*, i.e., where a team of followers is guided by multiple leaders see, e.g., [17–19]. Also motion in unknown environments carries about challenging control issues, such as obstacle border patrolling (see, e.g., [20,21] and reference therein) while, in the context of sensor networks, one of the major issues is *coverage*, i.e., to deploy a set of sensors so as to maximize the overall sensing performance, see, e.g., [22–25] and the references therein.

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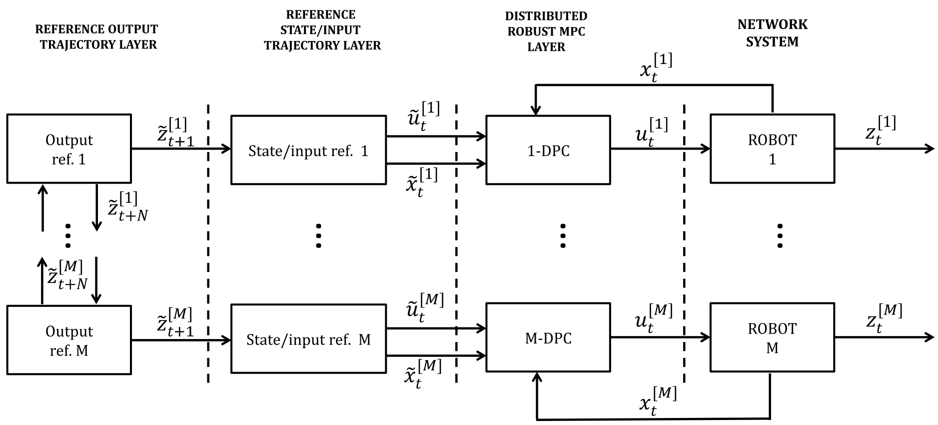

Fig. 1. The proposed multi-layer control architecture.

Despite the many results nowadays available, several issues still need to be addressed [9], if possible in a comprehensive fashion, such as the proper handling of constraints, the presence of input saturations, and the requirement of robustness. For these reasons, solutions based on robust Model Predictive Control (MPC) [3] appear to be promising. In fact constraints and limitations on the robot's dynamics and trajectory can be easily formulated as suitable constraints in the MPC optimization problem; distributed MPC solutions are currently available, see [1] and references therein, which, in a multi-robot environment, allow for the decomposition of the overall coordination control problem into smaller subproblems which can be locally solved on-board. This has significant computational and communication benefits with respect to centralized MPC solutions, and also confers flexibility and robustness to the overall system. However, the available MPC-based solutions guaranteeing robustness and collision avoidance properties (see e.g., [26,27], where notable real application experimental tests are also shown) are characterized by high dimensional and nonlinear optimization problems even in case of linear systems, which make them computationally demanding.

For all the above reasons, in this paper we propose a robust MPC approach for the solution of a number of motion and coordination problems. The method relies on the multilayer scheme shown in Fig. 1 and originally proposed in [2] for general interacting subsystems.

At the higher Reference Output Trajectory Layer of the control structure, and at any time instant t, an optimization problem is solved for any robot i to define the future reference trajectory $\{\tilde{z}_t^{[i]}, \dots, \tilde{z}_{t+N}^{[i]}\}$ to be followed for the solution of a number of motion and coordination problems, including formation control, coverage and optimal sensing, containment control, inter-robot and obstacle collision avoidance, and motion problems in an unknown environment. At the intermediate Reference State/Input Trajectory Layer, the state and control trajectories $\{\tilde{x}_t^{[i]}, \dots, \tilde{x}_{t+N}^{[i]}\}$ and $\{\tilde{u}_t^{[i]}, \dots, \tilde{u}_{t+N}^{[i]}\}$ compatible with $\{\tilde{z}_t^{[i]}, \dots, \tilde{z}_{t+N}^{[i]}\}$ are computed. Finally, at the lower Distributed Robust MPC Layer a robust DPC algorithm is solved to compute the robots' commands. Notably, at the intermediate and lower layers the algorithms are the same for all the considered problems. In the development of the method, effort has been devoted to state the optimization problems as quadratic ones, characterized by linear and computationally non-intensive constraints for collision and obstacle avoidance. This allows to cope with the usually limited on-board computational power and to enhance the reactiveness, in terms of reduction of sampling time, of the DPC algorithm.

The paper is organized as follows. In Section 2 it is shown how the unicycle robot model can be described using linear equations under a suitable feedback linearization procedure. Section 3 is the core of the paper: indeed, the obstacle and inter-robot collision avoidance problems are reformulated in terms of linear constraints, and the cost function to be minimized is customized in order to tackle different motion and coordination issues. Section 4 shortly describes the structure and the main characteristics of the DPC algorithm used at the lower layers, first proposed in [2], and here specifically tailored to the case of dynamically decoupled systems. In Section 5 we present the main theoretical result, regarding the recursive feasibility properties of the proposed control scheme. In Section 6 a sketch of the algorithm implementation is drawn and the choice of the main tuning knobs is thoroughly discussed. A number of simulation and experimental results in different scenarios, including formation control, optimal sensing, containment, border patrolling, are illustrated in Section 7. Finally, Section 8 draws some conclusions. The proofs of the main results are reported in the Appendix.

Notation. A matrix is *Schur* stable if all its eigenvalues lie in the interior of the unit circle. $\oplus$ and $\ominus$ denote the Minkowski sum and Pontryagin difference, respectively [28], while $\bigoplus_{i=1}^{M} A_i = A_1 \oplus \cdots \oplus A_M$. Where not specified, 2-norms are used, i.e., $\|\cdot\| = \|\cdot\|_2$; $\mathscr{B}_\varepsilon^{(dim)}(0) := \{x \in \mathbb{R}^{dim} : \|x\|_\infty \leq \varepsilon\}$ is a ∞-norm ball centered at the origin in the $\mathbb{R}^{dim}$ space. Given a two-dimensional vector $v = (v_x, v_y)$ on the Cartesian plane, the angle with respect to the x-axis is denoted by $\angle v$. For a discrete-time signal s_t and $a, b \in \mathbb{N}$, $a \leq b$, $(s_a, s_{a+1}, \dots, s_b)$ is denoted with $s_{[a:b]}$. I_n is the $n \times n$ identity matrix.

2. The robots

2.1. Model of the unicycle robots

We consider a set of M unicycle robots, whose dynamics is

$$\begin{cases} \dot{x} = v\cos\theta \\ \dot{y} = v\sin\theta \\ \dot{\theta} = \omega \\ \dot{v} = a \end{cases} \tag{1}$$

where v, a and ω are the linear velocity, acceleration and angular velocity, respectively, while (x, y, θ) denotes the position and orientation with respect to a fixed frame. The linear acceleration a and the angular velocity ω are the control inputs of the system.

2.2. Feedback linearization

A linear model of the robots is obtained with a feedback linearization procedure [29]. Defining $\eta_1 = x, \eta_2 = \dot{x}, \eta_3 = y,$

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