Cooperative Object Transportation With Non-holonomic Mobile Robots: Multibody Dynamics Meets Distributed Optimization

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EXTENDED ABSTRACT

1 Introduction

Thanks to rapid progress in communication technology and mobile computing power, networked robotics is expected to redefine what is possible with robotic automation, increasing productivity in logistics, manufacturing, security, and many other applications. Employing a network of robots that cooperate to solve tasks has plentiful advantages. For instance, efficiency can be increased since the number of robots employed can be adapted dynamically to the scale of the task. Moreover, if one of the robots breaks down due to a hardware failure, the network may compensate for that by restructuring or by bringing in a replacement robot. Yet, it is not easy to design methods and algorithms for true, distributed cooperation where decisions are actually made in a decentralized manner. Issues arising from concurrency [1] and from communication complicate method development compared to centralized approaches where all decisions are made by a single entity. However, to realize the promises of multi-robot systems, distributed decision making is required since a central decision maker would represent a single link of failure, scotching the intended robustness advantages. In this context, to drive methodological development, this contribution studies a model problem of distributed robotics in the form of cooperative object transportation. There exist variants of the problem, see, e.g., the overview provided in [2]. In the variant studied here, the robots are not rigidly attached to the object and can only push the object. Transportation schemes available so far usually study very limited object shapes like boxes or ellipsoids [2] and sometimes use omnidirectional mobile robots that can accelerate in any direction independent from their orientation. In contrast, the transportation method proposed in this contribution can automatically accommodate arbitrary polygonal objects and uses differential-drive mobile robots, which are simple to build but complicate motion planning due to their non-holonomic kinematic constraint. A photograph of one of the robots employed in this study is provided in Figure 1. Indeed, using such robots for the transportation task presents a rather timely issue; for instance, in [3], also the usage of differential-drive robots for the transportation of more general object shapes is considered but proper consideration of the robots' non-holonomic constraints is left for future work.

2 Methodology

This contribution's transportation scheme is based on our previous scheme for omnidirectional mobile robots presented in [4], which, to the knowledge of the authors, is the most versatile hardware-validated transportation scheme with distributed decision making. Characteristically, our method is model-based and uses distributed optimization for decision making. The model-based character is a key reason why the scheme can automatically adapt to all objects that can be approximated by polygons (including curved objects) and to any number of robots; alternative schemes, e.g., based on reinforcement learning as in [5], would need to be retrained or manually reconfigured for different shapes. We divide the transportation problem into the two sub-problems of dynamic control and of finding robot formations around the object that can be used to push the object as currently desired. The former needs to be solved reliably at a fast sampling rate, whereas the latter is more computationally intricate and can be solved asynchronously since the robots can wait until an appropriate formation is available. To obtain useful formations, given a desired motion of the object, a multibody model is formulated for the system consisting of robots and object, including the contact constraints between robots and object and the robots' non-holonomic kinematic constraints. This is then used in the constraints of an optimization problem to ensure that there exists a set of motor torques that lets the robots push the object so that it is accelerated as required while the robots stay in contact with the object. The cost function of the optimization problem prefers formations

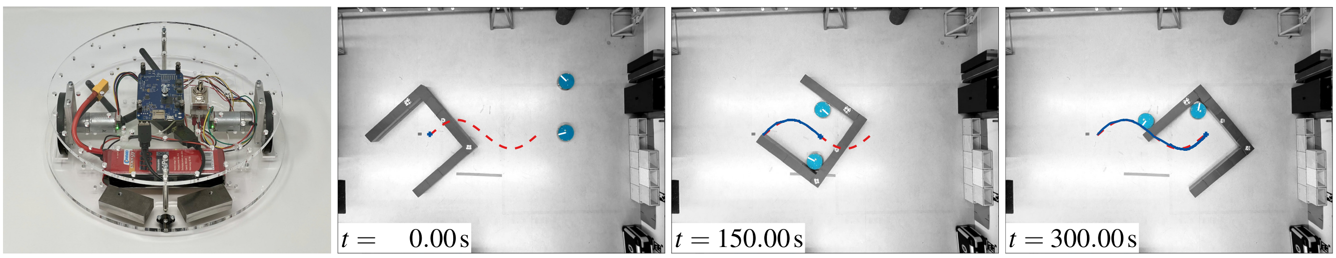

Figure 1: Photograph of one of the employed differential-drive robots (left), and images from an experimental result where the object's center of mass, whose trajectory is depicted as a solid blue line, shall follow the reference path dashed in red.

that also work for transportation directions around the currently desired one so that the robots may reorganize less frequently. The resulting problem is solved with distributed augmented Lagrangian particle swarm optimization [6, Section III.B] so that, for each robot, one cooperating solution agent is running. We tested the general idea for formation finding already in previous work [7], but only in idealized simulations where the robots organize instantly into the formation, mostly neglecting intricacies of dynamic control and real-world experiments but showing that the chosen formations are actually useful for transportation. This contribution goes beyond that by considering realistic simulations and real-world experiments. To that end, also dynamic control is inspected in detail. The proposed approach uses model predictive control (MPC) since that allows to directly incorporate constraints and a model of the robots to arrive at an easy-to-tune and well-behaved controller. First, each robot moves into position using an individual MPC controller and, when all robots have signaled one another that they are ready, the robots use distributed model predictive control (DMPC) to jointly move the object. DMPC, again, relies on distributed optimization. However, formulating functioning MPC controllers even for individual non-holonomic robots is a surprisingly intricate task. The usual approach, which employs a quadratic cost function, is proven to not work properly [8]. Even using tailored theory to design controllers fitting to the geometry arising from the robots' non-holonomic constraints can be problematic since the large backward-forward motions performed by the controller to compensate for lateral errors can make the robots crash into the transported object in the individual control phase when moving into formation. This contribution shows how the cost function can be set up to lead to a convergent controller while preventing detrimental backward-forward motions. The main idea is to evaluate the control error in a time-variant coordinate frame that rotates with the direction of the vector pointing from the robot to its aim position while penalizing the control error in the x- and y-directions of that frame in different ways, yielding a non-quadratic cost function. Similar attention has to be paid when designing the distributed formation controller. The variant pursued in this work is to only penalize control inputs that lead to linear motion whereas rotation is left cost-neutral. Intuitively, this always makes it worthwhile for the robots to rotate into the direction most useful to reduce the control error. Otherwise, the cost for rotation may be too significant to even start moving.

3 Results

This contribution tests the proposed scheme in several realistic simulations and hardware experiments. Still images from an experimental result are printed on the right-hand side of Figure 1. Indeed, the results show that differential-drive robots can attain a similarly satisfactory transportation performance as omnidirectional mobile robots did in our previous work. As for those, transportation performance seems mostly limited by wheel slip, which reduces the attainable pushing forces. This is exacerbated by the fact that the control scheme works on a kinematic level, with the robots being unable to measure the forces they exert on the object. A more delicate manipulation of the object may be possible if force sensors are mounted to the robots and if their measurements are used in the control loop. This is a subject of our future research.

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