A Distributed Method for Estimating the Grasping and Inertial Parameters in Cooperative Manipulation

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Introduction

The cooperative manipulation problem involves the contribution of n robots to grasp a payload B of arbitrary shape in order to move it, *e.g.*, from an initial position to a final one (see Fig. 1). The majority of the works concerning cooperative manipulation algorithms in literature are based on the assumption of the *a priori* knowledge of the geometric and inertial parameters of the manipulated object, although this assumption is not always verified in real world scenario. To cope with this issue, we propose a novel distributed algorithm for the estimation of the grasping and inertial parameters of an unknown load [1].

Problem statement

We consider a load modeled as a planar rigid body, whose center of mass is denoted with C. The load is manipulated by a group of n mobile robots, where each robot can exert a force on a contact point C_i. Consider a planar reference inertial frame $\mathcal{W} = \{O_{\mathcal{W}} - x_{\mathcal{W}}\, y_{\mathcal{W}}\}$ and denote with $\mathbf{p}_C \in \mathbb{R}^2$ the position of C in $\mathcal{W}$, with $\mathbf{p}_{C_i}$ the position of C_i in $\mathcal{W}$ and with $\mathbf{f}_i$ the force applied by the i-th robot at C_i and expressed in $\mathcal{W}$, where $i = 1, \ldots, n$. The dynamical model of the load B is therefore the following:

$$\ddot{\mathbf{p}}_C = \frac{1}{m}\sum_{i=1}^{n}\mathbf{f}_i \tag{1}$$

$$\dot{\omega} = \frac{1}{J}\sum_{i=1}^{n}(\mathbf{p}_{C_i} - \mathbf{p}_C)^{\perp\,T}\mathbf{f}_i, \tag{2}$$

where $m > 0$ is the mass of B, $\omega \in \mathbb{R}$ is its angular velocity, $J > 0$ is its moment of inertia, and the operator $(\cdot)^\perp$ is the linear operator, that, given a generic vector $\mathbf{v} \in \mathbb{R}^2$, $\mathbf{v} = (v^x \;\; v^y)^T$, provides the perpendicular vector $\mathbf{v}^\perp = (v^y - v^x)^T$. Each robot is able to control the force applied to the load and to measure the velocity of the force contact point. Furthermore, robots are able to communicate via a one-hop wireless network.

The Algorithm

The aim of the algorithm is to estimate the inertial parameters of the load, such as the mass, the moment of inertia, and the position of the contact points with respect to the center of mass, in order to improve the performance of the control strategy. The estimation of the latter requires the estimation of the relative positions of the contact points and of the center of mass relative to the geometric center of the contact points. A fundamental assumption is that each robot cannot measure the position of any contact points, nor their accelerations. The algorithm consists of 7 steps.

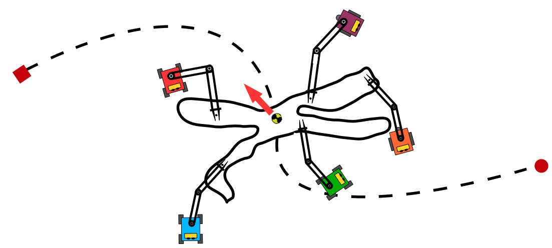


Figure 1: Cooperative manipulation: the estimation setup.

Step 1: As a preliminary step, each robot uses the measurement of its own velocity and that of its neighbors (received over the communication network) in order to obtain, in a distributed fashion, an estimate of the relative positions of the contact points.

Step 2: In the second step, each robot uses the relative position measurements to compute, using the algorithm in [2], the relative position between the contact point and the geometric center of all the contact points.

Step 3: Then, each robot computes, locally, the angular velocity of the load on the basis of the relative positions of the contact points and the velocities of the contact points of its neighbors.

Step 4: Thus, each robot applies a suitably computed force and observes the angular velocity of the payload. By means of an average consensus algorithm [3], each robot knows the value of the sum of the applied forces. This allows each robot to reach an estimate of the moment of inertia.

Step 5: In the fifth step, each robot applies the same constant nonzero force and measures the angular velocity. In order to agree on the same value of the applied force, a suitable consensus protocol is used. Then, it is possible to prove [1] that the estimation of $\mathbf{z}_C = \mathbf{p}_C - \mathbf{p}_G$, *i.e.* the position of the center of mass relative to the geometric center of the contact points, is equivalent to observe the state of

$$\begin{cases} \dot{x}_1 = -x_2 x_3 \\ \dot{x}_2 = x_1 x_3 \\ \dot{x}_3 = x_1 \bar{f}_y - x_2 \bar{f}_x + \eta \\ \;\; y = x_3, \end{cases} \tag{3}$$

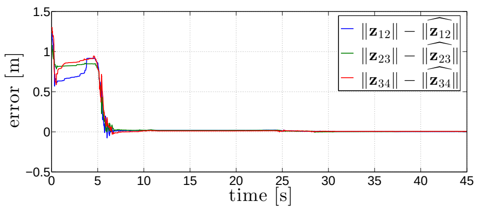


Figure 2: Estimation errors of the distances between neighbors.

where we let $z_C^x = x_1$, $z_C^y = x_2$, $\omega = x_3$. Moreover, it is possible to prove [1] that the following dynamical system

$$\begin{aligned}\dot{\hat{x}}_1 &= -\hat{x}_2 x_3 + \bar{f}_y(x_3 - \hat{x}_3)\\ \dot{\hat{x}}_2 &= \hat{x}_1 x_3 - \bar{f}_x(x_3 - \hat{x}_3)\\ \dot{\hat{x}}_3 &= \hat{x}_1 \bar{f}_y - \hat{x}_2 \bar{f}_x + k_e(x_3 - \hat{x}_3) + \eta,\end{aligned} \quad (4)$$

is an asymptotic observer for system (3). Then, each robot is able to obtain an estimate that eventually converges to the time-varying vector $\mathbf{z}_C$, by means of the observer together with the estimated moment of inertia.

Step 6: At this time, each robot is able to compute the position of the contact points relative to the center of mass. Then, the velocity of the center of mass can be computed locally by any robot.

Step 7: In the last step, each robot applies the same constant nonzero force and measures the velocity of the center of mass. In order to agree on the same value of the applied force, a suitable consensus protocol is used. This allows each robot to agree on an estimate of the payload mass.

Further information can be retrieved in [1]. Moreover, the effect of noise on the algorithm is accounted for in [4], where an approach based on *Least Squares* filters is used.

SIMULATION RESULTS

We test the proposed algorithm by means of numerical simulations. We simulate a rigid body of mass $m = 5$ kg and a moment of inertia $J = 8.6891$ kg m^2 manipulated by $n = 4$ mobile robots. We assume that the robots can exchange information over a line topology network. The measurement noise is assumed to be Gaussian with zero mean and covariance matrix $\Sigma_i = \sigma^2\mathbf{I}$, with $\sigma = 0.2$ m/s, and where $\mathbf{I} \in \mathbb{R}^{2\times 2}$ is the identity matrix. The trend of the estimation error of the relative distances between the contact point is depicted in Fig. 2, while the observation of the time-varying position of the center of mass relative to the geometric center of the contact points is given in Fig. 3. The result of the estimation of the mass and of the moment of inertia are reported in Fig. 4. It is evident as each robot of the network converges to the same value, respectively, $\hat{m} = 4.8517 \pm 0.0113$ kg and $\hat{J} = 8.7183 \pm 0.0004$ kg m^2.

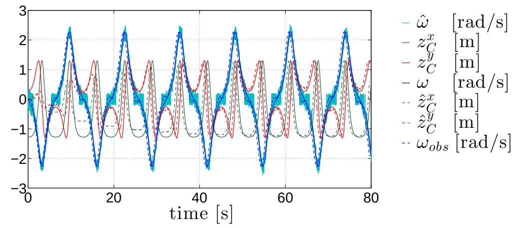
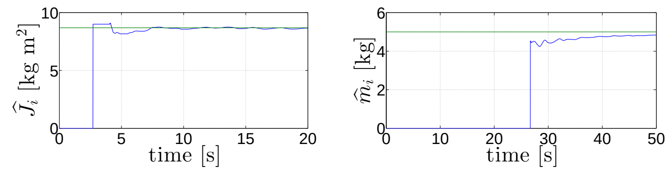


Figure 3: Observation of the vector $\mathbf{z}_C$ and of the angular rate ω.



(a) (b)

Figure 4: Estimation (a) of the mass m and (b) of the moment of inertia J.

FUTURE WORK

Future work will focus on two main topics: the extension of the proposed approach to the 3D case (for real-world manipulation applications using aerial or underwater multi-robot systems), and the design and implementation of manipulation control strategies based on the distributed estimation of the inertial parameters. The proposed algorithm is not suitable to the 3D case. Indeed, the transition to the 3D case involves a problem of scale due to the use of differences in velocity measurements, *i.e*, the vector resulting from the difference of two velocities in the 3D case can not be associated unequivocally to a given value of distance between two points (as we assume in the Step 1 of the aforementioned procedure). Due to this different problem setting, the design of a novel procedure is a challenging and interesting problem. The knowledge of the inertial parameters is a prerequisite in order to be able to perform cooperative control algorithms for manipulation. The benefits provided by on-line estimation techniques are twofold: first, effective control techniques for manipulation, like force control and pose estimation, can be applied in order to achieve better performance with a reduced control effort; second, manipulation of loads with time-varying characteristics can be achieved (for instance, in transport application it is not rare that the payload is increased by an external cause, or that part of the load is lost during the transportation). Thus, the design and implementation of novel distributed cooperative control technique, such as adaptive control approaches as well as event-driven control algorithms, will be achieved exploiting the effectiveness of the real-time estimations.

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