Cooperative Multi-Robot Control for Target Tracking with Efficient Switching of Onboard Sensing Topologies

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I. Introduction

Using multiple robots to track a moving target is potentially beneficial because of the reduction in tracking uncertainty, increased coverage, and robustness to failure. Two problems arise immediately. First, these objectives are often at odds (e.g., the configuration of the robots that lead to the lowest uncertainty estimates of target pose may not be the best if one or more robots is disabled). Second, the robots themselves are often poorly localized (e.g., only a few may have access to GPS, and the rest may be limited to a combination of onboard inertial sensing, visual odometry, and relative range/bearing measurements to estimate their poses relative to each other).

In the domain of cooperative control, small unmanned aerial vehicles (UAVs) have recently become prominent in multi-robot control with motion capture state estimates [5, 7]. For cooperative target tracking with onboard sensors, researchers considered centralized [3], decentralized [1], and distributed [4] approaches to multi-robot control in aerial and ground settings. However, these methods estimate the pose of the target and assume that the poses of the robots are known, e.g., from an external system or by reference to a global map. To robustly perform cooperative multi-robot localization using only onboard sensors, optimization-based maximum-likelihood localization approaches have been proposed [2]. However, it does not allow for direct minimization of the uncertainty associated with the estimated target pose.

In this paper, we consider the cooperative control of a team of robots to estimate the position and minimize the position uncertainty of a target using onboard sensing. In particular, we assume limited sensing capabilities and reason over the entire sensing topology by explicitly estimating the joint state of the robots and target.

II. Multi-robot Control with Topology Switching

1) Sensing Topologies: At each time step, the team of robots is in a certain topology with respect to sensing. In our multi-robot control method, we efficiently organize sensing topologies by applying a level-based approach. Each robot is assigned to a level, the global sensor is in the highest level, and the target is in the lowest level (see Fig. 1). Each sensor can potentially observe each robot/target in the adjacent layer below it given that its capabilities allow the corresponding measurements in the spacial configuration.

During target tracking, we allow switching between neighboring topologies. We consider two sensing topologies as neighbors, if the team can transition between them by just moving one robot by one level up or down (which can result in adding or removing a level).

2) Extended Kalman Filter (EKF) State Estimation: We use the popular EKF to efficiently and robustly estimate the joint pose of all robots and the target from imprecise movements and noisy measurements similar to [6]. The motion and sensing functions, their Jacobians, and the noise covariances are provided by the motion and sensor model of each entity, respectively.

3) Optimization-based Control: We formulate the selection of controls as an optimization problem with the cost function at time step k:

$$c_k(\mathbf{u}) = \sum_{i=1}^{h} \gamma^i \operatorname{tr}(\Sigma'_{k+i}) \; . \tag{1}$$

It penalizes the uncertainty of the state estimate of the target in terms of the trace of the marginal Σ' of the covariance Σ of the joint EKF, given the control $\mathbf{u}$ is applied for h time steps in the EKF, where $0 \leq \gamma \leq 1$ is a discount factor. In our approach, we apply nonlinear optimization to find the locally optimal control $\mathbf{u}_k^\star = \operatorname{argmin}_{\mathbf{u}} c_k(\mathbf{u})$ for the current topology and all neighbor topologies. We then select the topology and corresponding control that resulted in the lowest cost.

The asymptotic complexity of our approach with n robots is $O(n^5)$, since each EKF evaluation has cubic complexity and is nested in the optimization and the evaluation of neighboring topologies, which both have linear complexity.

III. Experiments

A. Simulations

We evaluated our approach on a number of simulations. We consider robots and a target as points moving in 2D space, and we employ the Kalman filter to estimate their positions. The global sensor (called GPS) is located at the origin $[0, 0]$. All sensors provide omnidirectional relative position measurements with a range of 0.5 m.

An example of the simulation results is shown in Fig. 1; a video is available online[1]. While the controls selected by

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[1] http://robotics.usc.edu/~hausmankarol/videos/iser_videos

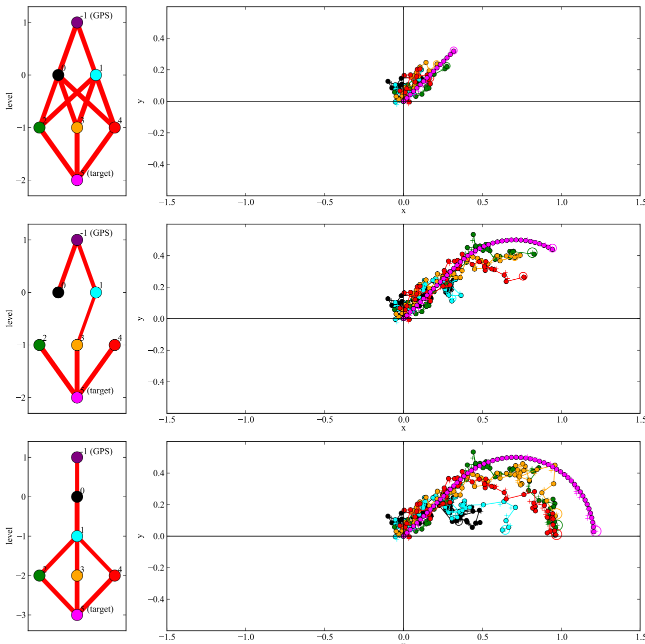

Fig. 1. Simulation results with 5 robots. Left: the current topology selected by our approach. The links represent the actual measurements where the thickness of each link corresponds to the information provided by the measurement. Right: The trajectory and the state estimates of the EKF. The actual trajectory is shown as thick dots connected by a solid line. The EKF means are indicated by '+' and the covariance is shown for the current state.

the approach were quite smooth, the zigzag movements of the robots were due to the simulated motion noise. Each experiment started in one of the simplest topologies, in which the robots were arranged as a string, each residing on its own level. Our approach locally modified the topology during the first steps and converged to a topology with two levels (Fig. 1, row 1). As the target moved away from the GPS signal, the limited measurement range causes dropouts (row 2) and our approach introduced an additional robot level (row 3). Further simulations with 2 to 30 robots and different sensor models confirmed that the selected topologies depend on the limitations of the sensor model.

B. Real Robot Experiments

We implemented and tested the approach on Parrot AR.Drone quadrotor UAVs shown in Fig. 2. The setup consists of a camera at the ceiling as a global sensor, and a TurtleBot 2 as a moving target on the ground. Each AR.Drone is equipped with an inertial measurement unit (IMU), an ultrasound altimeter, two cameras, and WiFi communication. The down-looking camera is used internally to estimate the visual odometry, which is fused with the IMU and altitude information of the quadrotor. We modified the forward-looking camera to be tilted $45°$ downwards to track other robots and the target, all equipped with checkerboard markers for relative pose estimates.

We conducted a series of real robot experiments as a proof of concept of our approach; the videos are available online[1]. Fig. 2 shows two robots that are tracking the target and are currently in the string topology where each robot resides on

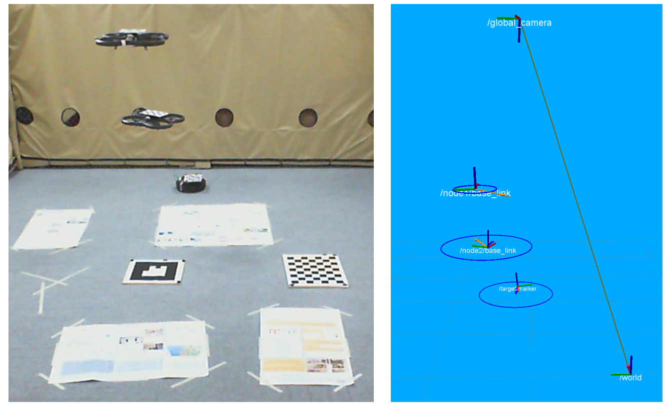

Fig. 2. Two AR.Drones tracking the target – currently in a string topology. The state estimates are shown as blue arrows, the corresponding covariances are represented by blue ellipses. The commanded velocities are shown as orange arrows.

its own level. Although the target went temporarily out of the robot's field of view, the system was able to recover and continue tracking.

IV. Conclusions

We presented a probabilistic multi-robot control approach that considers onboard sensing and topology switching for target tracking. Our method generates locally optimal control while keeping polynomial complexity. We evaluated our approach in a number of simulations and showed experiments with inexpensive quadrotor robots as a proof of concept. Our approach proved to flexibly adapt the topology and controls to the sensing limitations of the individual robots and the target movements. At present, we restrict this search using a neighbor heuristic. In the future, we plan to further explore principled topology switching techniques that preserve scalability.

References

[1] E. Adamey and U. Ozguner. A decentralized approach for multi-UAV multitarget tracking and surveillance. In *SPIE Defense, Security, and Sensing*, 2012.

[2] A. Ahmad, G.D. Tipaldi, P. Lima, and W. Burgard. Cooperative robot localization and target tracking based on least squares minimization. In *Proc. of the IEEE Int. Conf. on Robotics & Automation (ICRA)*, 2013.

[3] B. Charrow, V. Kumar, and N. Michael. Approximate representations for multi-robot control policies that maximize mutual information. In *Proc. of Robotics: Science and Systems (RSS)*, 2013.

[4] B. Jung and G.S. Sukhatme. Cooperative multi-robot target tracking. In *Distributed Autonomous Robotic Systems 7*, pages 81–90. Springer, 2006.

[5] S. Lupashin, A. Schollig, M. Sherback, and R. D'Andrea. A simple learning strategy for high-speed quadrocopter multi-flips. In *Proc. of the IEEE Int. Conf. on Robotics & Automation (ICRA)*, 2010.

[6] A. Martinelli, F. Pont, and R. Siegwart. Multi-robot localization using relative observations. In *Proc. of the IEEE Int. Conf. on Robotics & Automation (ICRA)*, 2005.

[7] N. Michael, D. Mellinger, Q. Lindsey, and V. Kumar. The GRASP multiple micro-UAV testbed. *IEEE Robotics & Automation Magazine*, 17(3):56–65, 2010.