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Formation control driven by cooperative object tracking

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HIGHLIGHTS

- Formation control with dynamic formation geometry.
- Goal is to minimize the uncertainty about the cooperative observation of a target.
- Uncertainty term is part of a cost functional minimized by the formation geometry.
- Cooperative target estimator based on a particle filter.
- Simulated and real heterogeneous robot results (indoors and outdoors).

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ABSTRACT

In this paper we introduce a formation control loop that maximizes the performance of the cooperative perception of a tracked target by a team of mobile robots, while maintaining the team in formation, with a dynamically adjustable geometry which is a function of the quality of the target perception by the team. In the formation control loop, the controller module is a distributed non-linear model predictive controller and the estimator module fuses local estimates of the target state, obtained by a particle filter at each robot. The two modules and their integration are described in detail, including a real-time database associated to a wireless communication protocol that facilitates the exchange of state data while reducing collisions among team members. Simulation and real robot results for indoor and outdoor teams of different robots are presented. The results highlight how our method successfully enables a team of homogeneous robots to minimize the total uncertainty of the tracked target cooperative estimate while complying with performance criteria such as keeping a pre-set distance between the teammates and the target, avoiding collisions with teammates and/or surrounding obstacles.

1. Introduction

Most of the past and current work on motion coordination of multiple (possibly heterogeneous) vehicles [1,2] focuses on controlling a vehicle formation with a given nominal geometry and a pre-determined trajectory or a static destination location, in some cases more [3] or less [4] compliant with the presence of obstacles on the formation trajectory. Such methods typically:

- assume full knowledge of the formation state, expressed as the relative distances and bearings among all the vehicles, and/or
- rely on local memory-less interactions, often jeopardizing global formation stability.

A vehicle formation is supposed to serve one or more mission objectives [5]. One such interesting case concerns localizing or tracking relevant objects, here and henceforth denominated as targets. Recent formation control methods go beyond simply stating the desired geometry for the formation by providing some meta-specifications (e.g., for velocity matching, connectivity maintenance and containment control among the formation members [6,7]) but often give little or no relevance to the requirements

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imposed by target localization and/or tracking to the formation geometry, so as to improve the target detection and tracking quality (e.g., accuracy). Active cooperative perception methods in sensor and robot networks [8] concern precisely this problem: how to actively move mobile sensors so as to improve the accuracy of target detection by the network, as the result of (spatially and temporally) fusing the information from all the static and mobile sensors which observe the target during a step sequence. In this paper we propose an integrated solution of the "target localization and tracking by a vehicle formation" problem, supported on the following novel contributions:

- a cooperative target tracker based on a particle filter (PF) which estimates the target position and velocity;
- a non-linear model-predictive formation controller, with the control objective of efficiently tracking a target based on cooperative perception while achieving criteria such as minimizing the uncertainty about the target position, keeping a pre-set distance to the tracked object and/or avoiding collisions between teammates in the formation while tracking the target.

Therefore our solution integrates two basic modules: (i) controller and (ii) estimator.

Our controller consists of a distributed non-linear model predictive controller (DNMPC). Some predominant approaches in multi-robot formation control are: virtual structures, behavior-based and leader-following [9–11]. A widely used controller based on the leader-following approach is the model predictive controller (MPC) [12] which was recently introduced in holonomic robots [13]. The primary focus of most existing methods is only to maintain the formation based on pre-planned paths and static environment assumption. In a dynamically changing environment, if the trajectories are pre-defined, linear MPC applied to a non-linear system can still maintain a desired formation.

Recent approaches for active cooperative target tracking by a robot team formation such as [8] rely on computationally heavy optimization processes. By introducing the Gauss–Seidel relaxation in an iterative algorithm to detect the next best sensing location for the mobile sensors, the authors in [8] achieve a linearly growing computational complexity over methods like grid-based exhaustive search which have similar tracking accuracy but where the complexity grows exponentially with the number of sensors. The novelty in our approach of integrating the controller and estimator modules to achieve a formation that minimizes the joint uncertainty covariance of the tracked target lies in the fact that the controller module of each robot performs an optimization over an already fused target posterior which makes the computational complexity of the optimization process constant with respect to the number of mobile sensors in the team. Furthermore the decoupling of the optimization problem from the estimates fusion makes the approach more reliable in case of individual sensor or inter robot communication failures.

The field of cooperative target tracking has gained a lot of attention in the recent years [14–16]. Many efficient solutions such as decentralized PF for multiple target tracking [15] and global position sharing based on non-egocentric tracking of objects [16] have been proposed. These solutions focus more on compacting the data shared for communication bandwidth reduction and to overcome the problem of target occlusion. Some solutions such as [17] assume multiple static platforms and hence do not address the self-localization errors that creep in when using multiple mobile sensor platforms. The estimator in our work consists of a cooperative target tracker based on a PF described in full detail in previous work [18,19]. Essentially the core of it is a PF, modified to handle, within a single unified framework, the problem of complete or partial occlusion for some of the involved mobile sensor platforms, as well as inconsistent estimates in the global frame among sensors, due to observation errors and/or self-localization uncertainty of the sensor platforms. This acts as a feedback module providing the position and velocity estimates of the tracked object to the controller which in turn uses these estimates as well as the teammate positions to generate velocity set points for the robot running the integrated system.

The robots in our formations share information over wireless communication, which, given its low reliability, is another source of errors that increase cooperative perception noise. Beyond uncontrollable interferences inherent to the operational environment, typical wireless communication protocols are also subject to transmission collisions that lead to packet losses, which are particularly relevant when the robots share their states periodically in broadcast mode. Thus, we use a communication protocol that auto-synchronizes the robot transmissions over the wireless medium, reducing collisions and improving the quality of the communication. We built upon the work in [20] to extend such protocol to ad-hoc networks that are better suited to robot teams [21]. We also used this protocol to provide an alternative relative localization system based on RF-ranging [21] later combined with signal strength information for faster localization assessment. The actual information sharing is carried out over a distributed shared memory middleware called Real-Time Data Base (RTDB) [22], which decouples local processing from communication delays and provides fast access to remote data with age information.

The rest of the article is organized as follows. The controller and the estimator modules are detailed in Section 2. Then we describe their integration in Section 3. This is followed by our approach's implementation details on our testbed and the experimental results in Section 4. We conclude with comments on future work in Section 5.

2. The controller and estimator modules

2.1. Controller module

The distributed non-linear model predictive controller (DNMPC-)based formation controller used in this work has its roots in the non-linear model predictive controller (NMPC) developed and implemented in one of our previous works [23]. NMPC has a partially distributed architecture where each robot calculates its own control inputs U solving its own optimization problem, and using a central unit only as a communication bridge. In the fully distributed architecture of the DNMPC the communication is performed by a real-time data base (RTDB) system [21]. This enables the robots to be communication-failure tolerant. Furthermore, even in the rare case of a communication failure, the robots use their predictive open-loop strategy to determine their teammate states making the DNMPC even more robust.

The DNMPC ability to create and maintain a formation is due to the fact that the cost functions used by the controllers of each robot in the team are coupled. This coupling occurs when the teammate states (position and velocity) are used in the cost function of each robot controller to enforce the desired formation geometry, thus the actions of each robot affect its teammates. The DNMPC iterates through the following two components:

- **optimizer**: uses an online numeric minimization method to optimize the cost function and generate the control signals. The resilient propagation (RPROP) method that is used here guarantees quick convergence;
- **predictor**: predicts the state evolution based on the system state model. The system consists of the robot itself, its teammates in the formation or another object in the environment with an impact on the formation objectives, such as a static obstacle or a moving target.