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Multi-robot cooperative spherical-object tracking in 3D space based on particle filters

Aamir Ahmad *, Pedro Lima

Institute for Systems and Robotics, Instituto Superior Técnico, Lisboa, Portugal

HIGHLIGHTS

- We present a cooperative approach to track a moving spherical-object in 3D space.
- Tracking is done by a team of mobile robots in a highly dynamic environment.
- Sensor fusion and occlusions are handled in a unified framework.
- We present a novel detection algorithm for spherical-objects in 3D space.
- We present results of real robot experiments with ground-truth comparison.

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ABSTRACT

This article presents a cooperative approach for tracking a moving spherical object in 3D space by a team of mobile robots equipped with sensors, in a highly dynamic environment. The tracker's core is a particle filter, modified to handle, within a single unified framework, the problem of complete or partial occlusion for some of the involved mobile sensors, as well as inconsistent estimates in the global frame among sensors, due to observation errors and/or self-localization uncertainty. We present results supporting our approach by applying it to a team of real soccer robots tracking a soccer ball, including comparison with ground truth.

1. Introduction and related work

Tracking objects or people moving in large spaces, where the field of view of common sensors is relatively small when compared to the area being monitored, is better achieved by recurring to teams of cooperative sensors, either static or dynamic, e.g., mounted on mobile robots.

Object tracking is a field of research with multiple techniques being researched and developed extensively [1]. In recent years RoboCup Soccer has laid down a common platform for various research areas in robotics, object tracking being a predominant and crucial one. This involves tracking the soccer ball by the robots during the game play. The complexity of tracking has risen from small, orange colored balls to standard sized, random/multi-colored balls and from 2D to 3D [2]. The problem can be formulated as tracking a moving object of known dimensions by a moving robot. We use RoboCup Soccer as an ideal test-bed for novel methods that can be used outside soccer.

Particle Filters (PF) are one of the most popular methods employed for tracking [3]. PF are non-parametric filters. Non-parametric filters can efficiently handle multi-modal beliefs. In a generic tracker, which is also the case with our test-bed in this article, the motion model of object being tracked can be completely unknown and might change over time hence using a parametric filter can lead to failures quite often. This is because if we use any standard motion model for the object, the tracker can quickly result in low confidence on the posterior when the object motion changes to a different model or switches randomly. This makes it essential to have beliefs with multiple modes scattered over the whole state space. In the RoboCup scenario, PF-based trackers are currently being used by most of the teams. An interesting approach of fusing the Extended Kalman Filter (EKF) and Monte Carlo PF has been described in [4] where an integrated self-localization and ball tracking method is presented. In [5] a method for simultaneously estimating ball position and velocity using Monte Carlo Localization (MCL) is developed. An efficient implementation of

* Corresponding author. Tel.: +351 218418271.
E-mail addresses: aahmad@isr.ist.utl.pt (A. Ahmad), pal@isr.ist.utl.pt (P. Lima).

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Rao–Blackwellized PF which was successfully demonstrated on Sony AIBO robots in the four-legged league of RoboCup is presented in [3]. None of these works use the information from more than one sensor/robot, therefore being less robust to occlusion and very dependent on the relative state of the robot and the object tracked.

The field of sensor fusion, including its use for single and multiple target tracking [6,7], is now very mature. However, it does frequently address situations where the sensors are static, know their location in a global frame with no uncertainty, and occlusions occur rarely. When sensors are mobile, e.g., mounted on the top of mobile robots, their knowledge of their own localization may degrade over time and/or during time periods due to a number of reasons (e.g., absence of known environment features, bad odometry) and this impacts the uncertainty in the determination of the target position in the global frame, where it is fused with the estimates from the other sensors. Furthermore, occlusions can occur more frequently, as they are due not only to the target(s) path but also to the motion of the different sensors/robots. Therefore, the problem of cooperatively tracking a moving object by a team of mobile sensors is an extension of sensor fusion, designated here as cooperative perception, in which one has to handle occlusions, disagreements between sensors, and dynamic changes of the observation models due to frequent spatial changes.

Outside the RoboCup scenario, cooperative object tracking using a mobile robotic sensor network is explored in [8] where a new network routing algorithm is developed for faster intelligence sharing. In [9], a new cooperative perception architecture is developed and tested on multiple UAVs for forest fire detection and localization. A substantial effort is made developing the fire detector and fusion of data from various sensors used on-board a single and multiple UAVs. The errors that creep in due to the self-localization of the UAVs themselves are unaccounted for.

Efficient solutions for multiple static platforms and a moving target [10] or a single moving platform and moving target(s) [11] have been introduced. Our approach to combine both challenges, i.e., track a moving target using multiple moving platforms, is novel.

One problem often disregarded in sensor fusion, since most of the literature considers static sensors, is the uncertainty about the location of the sensors themselves. Moreover since fusing the information provided by the sensors requires a common reference frame, this is an important issue that cannot be ignored when the sensors move and are subject to temporary errors on their self-localization knowledge.

In [12] the relationship between fixed world objects and moving objects is explored for global object localization. These relationships are communicated to teammates where they form a set of constrained relations, solving which gives object location estimates. The authors in [13] present a cooperative PF-based tracker for Sony AIBO robots, where the fusion of information involves communicating a reduced set of particles between the robots over the wireless network, which still remains a huge dataset causing inefficient communication. Our approach overcomes this problem by performing the information sharing right at the observation/update step of the PF where, instead of particles, the observation model's parameters are communicated. Furthermore our approach incorporates localization and observation confidence to overcome issues of cooperative tracking, explained further in this paper.

In [6,7] a decentralized PF for multiple target tracking is developed and deployed on flight vehicles. The communication bandwidth problem is solved by transforming the particle set into a Gaussian Mixture Model (GMM) which seems to be an efficient way. In our work we communicate a single parametrized observation probability density function between two robots. This not only further reduces the bandwidth usage but also prevents the prediction model errors of the PF to be propagated to teammates which happens when sharing of particles (or of a parametrized form of it) is done.

Our work builds mainly upon [2,14], carried out in the direction of object tracking and sensor fusion among teammates respectively. In [2], a PF-based tracker is presented with a unique and novel 3-D observation model based on color histogram matching. Each robot has an individual tracker and its most notable feature is that the tracking could be performed in 3-D space without the object color information, but at the cost of computational expense. In [14] a sensor fusion technique for cooperative object localization using particle filters is presented. Parameters of a GMM approximating a teammate's tracker's particles are communicated to the other robots. Particles at a robot's tracker are then sampled using own belief and the received GMM.

In this paper, which is an extension our work [15], we introduce an approach to cooperative perception in 3D space where we implement a PF-based tracker. For each observing robot (i.e., a mobile robot with a sensor), we determine confidence factors associated to the tracked target from two origins: (i) the confidence on the observation itself and (ii) the confidence on the self-localization estimate of the observing robot. Note that the self-localization method itself is completely decoupled from the PF-based tracker. The observation model of each mobile sensor is a parametrized probability density function (e.g., a Gaussian centered on the observation). The probability density functions associated to the observations of the team robots are shared by all of them in a pool. Each robot selects the best function, i.e., the one with higher confidence factors, from the pool, and uses it to assign weights to the particles in the traditional PF update step. The parametrization of the observation models intends to reduce significantly the amount of data communicated to teammates, since the probability density function can be univocally represented by its communicated parameters. The method handles, within a single unified framework, inconsistencies (disagreements) between sensors due to observation errors and/or self-localization uncertainty. In order to achieve near real-time tracking, we developed a new 3D detection algorithm mainly because the detector presented in [2] is computationally expensive. The new detection algorithm which generates the observation model, eventually serving the update step of the PF-based tracker, uses a single dioptric vision system equipped with one fish-eye lens camera. To the best of our knowledge, this detection system in 3D for a spherical object of known size using a single camera is novel. The detection system assumes a prior information about the object's color but this constraint will be relaxed in the future work, as it depends mostly on the available computing power.

We implemented our approach of the cooperative tracking with the new 3D detection system on a team of soccer playing mobile robots to track a soccer ball of known size and color. In order to analyze the results we implemented a stereo vision based ground truth evaluation system described in [16]. This involves installing a pair of static cameras in positions from where each camera could observe the maximum possible spatial area of the test-bed. Intrinsic and extrinsic calibration of the cameras are done in order to detect the ground truth position of the ball in 3D within the test-bed area. The cooperative tracking results from each robot are then compared to their ground truth counterpart using this system.

In Section 2 we overview the PF and further explain how the PF-based tracker works. In Section 3 we introduce the fusion step and explain how we incorporate it in our PF-based tracker, the core of our work. In Section 4 the new method for object detection in 3D space is presented. Section 5 presents the details of the ground truth evaluation system based on stereo vision, describes the test-bed and presents real robots' experiment results compared with the ground truth. We conclude with comments on results and future work in Section 6.