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TDOA-based adaptive sensing in multi-agent cooperative target tracking

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ABSTRACT

This paper investigates the adaptive sensing for cooperative target tracking in three-dimensional environments by multiple autonomous vehicles based on measurements from time-difference-of-arrival (TDOA) sensors. An iterated filtering algorithm combined with the Gauss–Newton method is applied to estimate the target location. By minimizing the determinant of the estimation error covariance matrix, an adaptive sensing strategy is developed. A gradient-based control law for each agent is proposed and a set of stationary points for local optimum geometric configurations of the agents is given. The proposed sensing strategy is further compared with other sensing strategies using different optimization criteria such as the Cramer–Rao lower bound. Potential modifications of the proposed sensing strategy is also discussed such as to include the formation control of agents. Finally, the proposed sensing strategy is demonstrated and compared with other sensing strategies by simulation, which shows that our method can provide good performance with even only two agents, i.e., one measurement at each time.

1. Introduction

Target localization and tracking have been very important issues in the field of cooperative sensing and control by autonomous vehicles [1]. Instead of pre-deploying a large number of static sensor nodes covering a whole interested region, the task of target tracking can be fulfilled by using only one or serval mobile vehicles, which makes the system deployment much easier. Since static sensor nodes cannot change positions to improve its sensing performance dynamically, mobile robots are more frequently used to obtain the optimal sensing performance by autonomously and cooperatively adjusting their positions and communication topologies based on their knowledge about the targets [2,3].

In range or bearing based target tracking methods, the geometric sensor configuration formed by sensors and target can highly affect the tracking performance. In the literature, the optimal two-dimensional relative sensor–target geometry has been widely studied [4–6]. The Cramer–Rao lower bound (CRLB) has been a commonly used criterion for the optimal geometric configuration of sensors [4–10]. The optimal geometric configuration of sensor–target for bearing-only target localization is addressed with equal sensor to target ranges for all sensors in Nardone et al. [5], Kadar [9] and with arbitrary sensor to target ranges in Bishop et al. [6], Doğançay and Hmam [8]. The optimal geometric sensor–target configuration for range-based target localization is addressed in Bishop et al. [6], Martínez and Bullo [10]. The control of mobile sensors to track mobile targets while maintaining the optimal geometry is further investigated by minimizing the

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CRLB of target state estimate. However, the application of the CRLB requires a sufficient number of sensors to guarantee the invertibility of the Fisher information matrix. Some other optimization criteria are also considered in Gustafsson and Gunnarsson [4], such as a criterion based on the estimation error covariance matrix which includes the prior estimation information. In Huguenin and Rendas [11], the adaptive sensing for target tracking by mobile sensors is further addressed by minimizing the determinant of the estimation error covariance matrix. However, only a suboptimal sensing strategy is given, and the noises of different measurements are assumed to be independent, which is not applicable to cases such as the time-difference-of-arrival (TDOA) measurements based localization and tracking. In Doğançay and Hashemi-Sakhtsari [12], TDOA-based target tracking by a set of static sensors is considered using the recursive least-squares algorithm. In Zhou et al. [13], a local anchor-positioning method based on rotational TDOA measurement is proposed for building up an indoor position measurement system with static sensor networks. In Huguenin and Rendas [14], the adaptive sensing of a scalar environmental field by a group of agents is considered, which requires that the random measurement errors be bounded and gives asuboptimal solution for distributed implementation. However, the method cannot be applied where the measurement of each agent is not scalar and the measurement error is unbounded. For the estimation of target location, different sorts of methods have been proposed, such as the conventional extended Kalman filtering (EKF) method [15], iterated Kalman filtering (IKF) method [16], nonlinear least-squares method and maximum likelihood method [4]. A discussion of the connections between these methods can be found in Bell and Cathey [17]. The estimation of the time difference of signal arrivals has been studied in Blandin et al. [18], Dvorkind and Gannot [19].

In this paper, we investigate the adaptive sensing in three-dimensional cooperative target tracking by multiple autonomous vehicles based on measurements from TDOA sensors. The main contribution is that our method can be applied with an arbitrary number of agents that produce at least one measurement at each time. This decreases the cost of agent deployment and alleviates the request for a sufficient number of agents to make the Fisher information matrix invertible by using the CRLB. First, we apply the framework of Kalman filtering to iteratively estimate the target location which incorporates the Gauss–Newton method. Then, an adaptive sensing strategy is given by minimizing the determinant of the estimation error covariance matrix, and a gradient-based control law is derived for each agent to reach a local optimum position. A set of stationary points for local optimum geometric configurations of the agents is given. Furthermore, we discuss the connections between different optimization criteria including the CRLB. Potential modification of the algorithm is also given such as to include the formation control of agents for specific task requirement. The proposed adaptive sensing strategy still can provide good tracking performance with only two agents, i.e., with only one measurement at each time, for estimation of a three-dimensional target location.

The rest of the paper is organized as follows. In Section 2, we introduce the sensing model and some basic assumptions. An iterated estimation algorithm is given in Section 3. In Section 4, an adaptive sensing strategy for target tracking is proposed. The comparisons with other optimization criteria and potential modifications are discussed in Section 5. Simulation results are provided in Section 6. Section 7 is the conclusion.

2. Basic definitions and assumptions

Consider a target at position $s \in \mathbb{R}^3$, the dynamic model of which is given by

$$s_{k+1} = f(s_k, b_k, w_k),$$

where k is an integer denoting the discrete time instant, s_k denotes the value of s evaluated at time k and b_k is the target motion control input. In general, b_k is not known for an uncooperative target although some prior information about the input may be available. It can be estimated from information such as estimated velocity and acceleration. However, for the ease of expression, we assume that b_k is known, which in fact is not a limitation of our proposed method. The w_k is assumed to be a zero-mean white Gaussian noise and $\mathrm{E}[w_k w_l^{\mathrm{T}}] = \delta_{kl} Q_k$, where "T" denotes the transpose operation and δ_{kl} is the Kronecker delta. Q_k is assumed to be positive definite for all $k \geq 0$.

The same observation model as given in Bishop et al. [6] is applied in our research, i.e., at each time k, agent i at position $\mu_{i,k} = [x_{i,k}, y_{i,k}, z_{i,k}]^{\mathrm{T}} \in \mathbb{R}^3$ $(i = 1, 2, \ldots, N)$, paired with agent j, obtains a TDOA measurement given by

$$t_{i,j,k} = t_{i,k} - t_{j,k} = \frac{\| s_k - \mu_{i,k} \| - \| s_k - \mu_{j,k} \|}{\mathrm{v}} + \upsilon_{i,j,k},$$

where

$$t_{i,k} = \frac{\| s_k - \mu_{i,k} \|}{\mathrm{v}} + \varepsilon_{i,k},$$

$$\upsilon_{i,j,k} = \varepsilon_{i,k} - \varepsilon_{j,k}.$$

$\| \bullet \|$ denotes the Euclidean norm of a vector or matrix, $\mathrm{v} \in \mathbb{R}$ is the propagation speed of the signal emitted by the target which can be normalized as 1, $N \geq 2$ is the total number of agents and $t_{i,k}$ is the measurement of time of arrival of a signal received by agent i during the k-th sampling interval. $\varepsilon_{i,k}$ is assumed to be a zero-mean white Gaussian measurement noise subject to $\mathrm{E}[\varepsilon_{i,k}\varepsilon_{j,l}] = \delta_{ij}\delta_{kl}V_k$, where $V_k > 0$ for all $k > 0$. Thus, it is straightforward to get that $\upsilon_{i,j,k}$ is also a zero-mean white Gaussian noise with $\mathrm{E}[\upsilon_{i,j,k}\upsilon_{i,n,l}] = (\delta_{jn} + 1)\delta_{kl}V_k$.

Assuming that each agent has access to the information of any other agent in the network through direct or multi-hop communications, we only need to consider the TDOA measurements taken by one agent, e.g., agent 1, paired with all the other agents which form the measurement vector

$$\boldsymbol{t}_k = [t_{1,2,k}, t_{1,3,k}, \ldots, t_{1,N,k}]^{\mathrm{T}}.$$

Defining $h(s, \mu_1, \mu_i) = \| s - \mu_1 \| - \| s - \mu_i \|$ $(i = 2, 3, \ldots, N)$ and the following augmented variables:

$$\boldsymbol{\mu} = [\mu_1^{\mathrm{T}}, \mu_2^{\mathrm{T}}, \ldots, \mu_N^{\mathrm{T}}]^{\mathrm{T}},$$

$$\boldsymbol{\upsilon} = [\upsilon_{1,2}, \upsilon_{1,3}, \ldots, \upsilon_{1,N}]^{\mathrm{T}},$$

$$\boldsymbol{h}(s, \boldsymbol{\mu}) = [h(s, \mu_1, \mu_2), \ldots, h(s, \mu_1, \mu_N)]^{\mathrm{T}},$$