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Target tracking via recursive Bayesian state estimation in cognitive radar networks☆

Yijian Xiang[a], Murat Akcakaya[b], Satyabrata Sen[c], Deniz Erdogmus[d], Arye Nehorai[a,*]

[a] Washington University in St. Louis, St. Louis, MO 63130, USA
[b] University of Pittsburgh, Pittsburgh, PA 15213, USA
[c] Oak Ridge National Laboratory, Oak Ridge, TN 37831, USA
[d] Northeastern University, Boston, MA 02115, USA

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ABSTRACT

To cope with complicated environments and stealthier targets, incorporating intelligence and cognition cycles into target tracking is of great importance in modern sensor network management. With remarkable advances in sensor techniques and deployable platforms, a sensing system has freedom to select a subset of available radars, plan their trajectories, and transmit designed waveforms. In this paper, we propose a general framework for single target tracking in cognitive networks of radars, including consideration of waveform design, path planning, and radar selection, which are separately but not jointly taken into account in existing work. The tracking procedure, built on the theories of dynamic graphical models (DGM) and recursive Bayesian state estimation (RBSE), is formulated as two iterative steps: (i) solving a combinatorial optimization problem to select the optimal subset of radars, waveforms, and locations for the next tracking instant, and (ii) acquiring the recursive Bayesian state estimation to accurately track the target. Further, an illustrative example introduces a specific scenario in 2-D space. Simulation results based on the scenario demonstrate that the proposed framework can accurately track the target under the management of the network of radars.

1. Introduction

Target tracking has long been one of the most relevant and challenging problems in a wide variety of military and civilian radar systems. The primary objective of a conventional tracking system is to provide accurate estimates of an unknown target's state, e.g., its position and velocity. This can be done in a time-sequential manner by utilizing the received radar measurements and assumed target kinematic models. However, in modern tracking scenarios, it has become imperative to augment such stand-alone trackers with various intelligent and cognitive support-modules in order to successfully meet performance criteria [1–3]. Nowadays, the targets have become stealthier and more agile, and the tracking environments have become more complicated, involving numerous shadow regions due to the lack of line-of-sight propagation paths. In response, radar systems have evolved to include multiple static or mobile platforms that coordinate among themselves to improve the tracking accuracy. For example, tracking targets in urban environments using a fleet of self-controlled and self-tasked unmanned aerial vehicles (UAVs) is much more prevalent now than it was a few years ago.

To improve tracking performance in such complicated scenarios, a system of radars has to fully extract and utilize the environmental information, and intelligently manage its sensor (individual radars) resources. Therefore, in addition to using standard tracking filters, the radar system has to incorporate three key techniques: (i) *waveform design*, to extract more target information by adaptively designing transmitted signals, (ii) *path planning*, to obtain better "looks" at the target by actively adjusting the target-radar geometry, and (iii) *sensor selection*, to optimally select a subset of radars that can track targets with satisfactory performance. In this paper,

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* Corresponding author.
E-mail addresses: yijian.xiang@wustl.edu (Y. Xiang), akcakaya@pitt.edu (M. Akcakaya), sens@ornl.gov (S. Sen), erdogmus@ece.neu.edu (D. Erdogmus), nehorai@ese.wustl.edu (A. Nehorai).

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we develop a target tracking framework that enables simultaneous sensor subset selection, waveform design, and path planning to build a sophisticated tracking system.

1.1. Related work

A few works in the literature adopt one or combine two of the above three techniques in target tracking; however, no other work thus far has simultaneously applied waveform-agile sensing, planned the corresponding paths, and intelligently selected the subset of radars. For example, dynamic waveform adaption has been extensively investigated in target detection [4–10] and tracking [11–24] to meet a radar's constantly changing requirements for the target information. The motivation behind the adaptive waveform design techniques is to gain better tracking performance by integrating the radar transmitter and receiver in a closed-loop fashion. Previous works focus on analyzing the output of a matched filter and on improving the resolution [25] by treating the radar and tracker as independent subsystems [26]. In recent works, as the tracker recursively estimates the target state, the radar transmitter is adapted to design the next transmitted waveform according to a predefined utility function, such as the mean-square tracking error [15,16], the trace of the posterior Cramér-Rao lower bound (PCRLB) [11,27], and the mutual information [12,28,29]. In general, the utility function provides one-step ahead design (i.e., greedy); only a few articles discuss multi-step ahead waveform selection [15,30]. Some works directly design the frequency spectrum of the waveform by using optimal frequencies [4,5,31], while others select the waveform from a parameterized waveform library [29], such as a linear frequency-modulated (LFM) library [11]. Besides, waveform design for multistatic target tracking is also investigated [32]. Although waveform design and scheduling applications show promising results, they face challenges in selecting proper design metrics, designing optimal or nearly-optimal waveform families with respect to these criteria, and formulating computationally tractable scheduling policies [33].

Path planning is another important and fundamental issue for radars, particularly for those which are installed on moving platforms, such as UAVs. To improve the performance of target localization and tracking, careful design of radar paths to actively steer them to the optimal places within the kinematic capabilities [34–39] provides another degree of freedom in utilizing the feedback information from receivers. A simple case of obtaining the optimal trajectory of a single radar by maximizing the determinant of the Fisher information matrix in a passive bearings-only case for fixed target localization is introduced in [36]. Multiple radars cases are considered in [34,35,37–39], and cooperative path planning strategies are derived for both passive and active radars. However, in general, it is extremely complicated to plan the paths of multiple radars simultaneously under certain kinematic constraints while appropriately adopting non-myopic policies.

Sensor selection and resource allocation schemes are generally employed in sensor network management problems to intelligently assign a subset of sensors to accomplish the task with satisfactory performance or minimized usage of resources. A sensor selection problem is usually a combinatorial optimization problem, which can be NP hard to solve for the optimal solution, and therefore approximate techniques are necessary to search for an acceptable solution. In the literature, the sensor selection problem is usually cast in one of three ways. It can be formulated as a convex optimization problem with a heuristic searching method [40], as the maximization of a submodular function problem (which can be solved by a greedy algorithm with guaranteed performance) [41], or as a linear programming and a semi-definite programming (SDP) problem by respectively considering the measurement noises to be uncorrelated and correlated [42]. In regard to target tracking, the sensor selection and resource allocation schemes are adaptively applied from time to time [42–49].

In addition, a few works combine two of the three techniques (waveform design, path planning, and sensor selection) to further improve the tracking performance or decrease the resource usage. For example, waveform design and path planning are jointly considered in [24] and [50]. In [24], adaptive selection of the optimal pulse repetition interval (PRI) from a set of allowed values, and optimization of the radar trajectory using the trace of weighted PCRLB, are proposed, whereas [50] jointly optimizes the waveform parameters of Gaussian-LFM pulses and the guiding commands of multistatic radars using the trace of the PCRLB. Although multiple radars are taken into account, no subset selection strategy is adopted in [50], implying that the radars use all the available resources to track the target, which may lead to a waste of resources. In [51,52], waveform design and sensor selection are combined for static radars to select adaptive waveforms and a subset of sensors in accordance with the resource constraints. In our previous work [53], we proposed a framework of single target tracking based on the theories of DGM and RBSE, jointly considering radar selection and path planning. However, the advantages of the waveform-agility were not exploited to further improve the tracking performance and system intelligence.

1.2. Our contributions

In this paper, we propose a target tracking framework that simultaneously designs the transmit waveform, plans the radar trajectory, and selects the appropriate radar subset. Building on the established theories of dynamic graphical models (DGM) and recursive Bayesian state estimation (RBSE) [54,55], we choose the expected cross-entropy as the objective function and solve a combinatorial optimization problem to select the optimal subset of radars that transmit well-designed waveforms from their best locations for receiving the most informative measurements during the next tracking instant. The received measurements associated with history information are then processed by a tracker to achieve a more accurate target state estimation. Additionally, we validate the proposed framework by constructing an illustrative case, where radars with certain moving constraints track a single target in a 2-D space. Specifically, we choose this simplified case as it is a representation of a large-scale network of cognitive radars which have certain constraints about coverage area and path. As we describe later in Section 3, these constraints reflect real-time scenarios especially when each radar in the network is aware of the locations of the other radars in the network and when overlapping of coverage area among the radars along same path are avoided using the location information assuming that the target is in the far-field compared to all the radars in the network. Finally, simulation results are given to show the feasibility of the framework. The sensing system of the sensor network can achieve satisfying tracking performance with relatively low process noise.

Our main contribution in this paper is to consider the path design, waveform design and radar subset selection simultaneously in target tracking with a large-scale of network of radars. As we show with the numerical examples, under certain assumptions our method is computationally feasible and our approach is an important step towards the realization of a network of cognitive radars in real-time for target tracking. Even though the concept of cognitive radar has been proposed more than a decade ago [1], until now a real-time implementation of a cognitive radar has not been presented. The rest of paper is organized as follows. In Section 2, we present our framework for jointly selecting the subset of sensors and the corresponding waveforms with moving radars in target tracking. In Section 3, we give an illustrative example and solve the example based on the proposed framework. Further, experi-