



## Review Article

# Comparison of optimization algorithms in the sensor selection for predictive target tracking



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## ABSTRACT

This paper addresses the selection of sensors for target localization and tracking under nonlinear and nonGaussian dynamic conditions. We have used the Posterior Cramér-Rao lower Bound (PCRB) as the performance-based optimization criteria because of its built-in capability to produce online estimation performance *predictions*, a “must” for high maneuverable targets or when slow-response sensors are used. In this paper, we analyze, and compare, three optimization algorithms: genetic algorithm (GA), particle swarm optimization (PSO), and a new discrete-variant of the cuckoo search algorithm (CS). Finally, we propose local-search versions of the previous optimization algorithms that provide a significant reduction of the computation time.

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## Contents

1. Introduction . . . . .	183
2. System model. . . . .	183
2.1. Dynamic and observation model . . . . .	183
2.2. Tracking algorithm: Rao-Blackwellised particle filter . . . . .	184
3. Sensor selection . . . . .	184
3.1. Problem statement . . . . .	184
3.2. Fitness function: posterior Crámer-Rao Bound . . . . .	184
3.3. Optimization methods . . . . .	185
4. Discrete cuckoo search. . . . .	185
4.1. Cuckoo search . . . . .	185
4.2. Discrete Cuckoo Search Scheme . . . . .	186
4.3. Discrete Lévy Flights . . . . .	186
5. Global and local search . . . . .	187
6. Simulation results . . . . .	187
6.1. Results with global search . . . . .	188
6.2. Results with local search . . . . .	188
7. Conclusions. . . . .	190
Acknowledgment . . . . .	191
Appendix A. Observation model . . . . .	191

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Appendix B. Computing PCRB via Sequential Monte Carlo . . . . .	191
References . . . . .	191

## 1. Introduction

In this work, we investigate the centralized selection of ( $n_s$ ) sensors in target-tracking applications over huge networks where a large number ( $N$ ) of randomly placed sensors are available for taking measurements.

Obviously, the tracking accuracy improves with the increasing number of measurements. Therefore, in terms of the tracking performance, it is desirable to use as many measurements as possible. However, the nodes in the wireless sensor networks (WSNs) have limitations in energy consumption, computation power, and sensing ranges, which means that it is not optimal for all available sensors to take measurements. As a result, we have two conflicting goals: (1) to collect information of high quality (*utility*), and (2) to conserve energy (*cost*).

Several suboptimal heuristics have been proposed to approximately solve the sensor-selection problem. These include genetic algorithms [1], particle swarm optimization [2,3], convex optimization [4], or stochastic strategies [5].

Regarding the objective function (or, in other words, the utility function), the sensor selection can be based on entropy- or performance-related criteria [6].

With respect to the *entropy*-based utility functions, an uncertainty-bounded model was proposed in [7], where sensor information utility is related to the uncertainty area of target concerned with the sensors. This approach is good in precision but intensive in calculation. An entropy-based information utility measurement was also defined in [8]. This approach, implemented with Bayesian Filters, is based on the estimation of an expected target belief state. Although it achieves good tracking accuracy, it requires precise estimates for the probability density functions needed to obtain the information metric.

Regarding the *performance*-based utility functions, the Cramér-Rao lower Bound (CRB) provides the limit on the mean square error (MSE) for any unbiased estimator of the target state. This provides a powerful tool that, within the context of target tracking, has been used to assess the performance of estimators of track parameters for deterministic target motion [9]. In the case of dynamic and uncertain target motion, the Posterior Cramér-Rao lower Bound (PCRB) provides a measure of the achievable performance for recursive Bayesian estimators of the uncertain target state, with the added advantage of being independent of the estimation mechanism. In addition, it provides online estimation performance *predictions*, which are very useful both for tracking highly maneuverable systems and to activate slow-response sensors, as some used in environmental monitoring [10]. In [11,12], the authors demonstrated the utility of this criterion over information-based or entropy-based methods.

Optimization algorithms are proposed here as a solution to the sensor-selection problem. Many articles in the literature have used these algorithms in the field of WSN in many different ways [13,14]. For instance, the authors of [15] pose the optimization of the sensors placement to

achieve the optimal communication coverage, or as in [16] where its authors propose an energy-efficient routing based on optimization algorithms.

In this paper we focus on the application of optimization algorithms for the selection of sensors using the PCRB as a quality measure. The main part of this paper is devoted to the performance comparison of well-known optimization algorithms, such as the particle swarm optimization (PSO) [17] and the genetic algorithm (GA) [18]. We have also included the cuckoo search (CS) algorithm [19] in our study because it provides more robust and precise results than the PSO and the GA [20]. It is important to mention that the conventional CS algorithm cannot be directly applied to discrete search-space problems (as is the selection of  $n_s$  out of  $N$  sensors). For this reason, in this paper we present a modification (the Discrete Cuckoo Search, DCS) that, obviously, could be also applied to other discrete search-space problems.

Another contribution is related to computation of the PCRB and, therefore, of the target's vector state. There are many sensors that provide measurements that depend only on the target position (energy, time of arrival, gas concentration), and not (at least, directly) on its speed or acceleration. For this reason, and taking into account that the PCRB is not constrained by the estimation methodology, we propose to partition the state vector and to use the Rao-Blackwellized Particle Filter (RBPF) [21] in its estimation.

The rest of this paper is organized as follows. The system model and the applied tracking algorithm are explained in Section 2. In Section 3, we define the sensor-selection problem and its solution by means of optimization methods. Section 4 presents the discrete formulation of CS and its application to our problem. The use of a local search instead of a global search is proposed in Section 5. Simulation results are presented in Section 6. Finally, concluding remarks are presented in Section 7.

## 2. System model

### 2.1. Dynamic and observation model

The aim of target tracking is to estimate the state trajectories of a movable element. Although a target is almost never really a point in space and the information about its orientation is valuable for tracking, a target is usually treated as a point object without a shape in tracking, especially in target dynamic models. Under the usual Markov assumption, the standard discrete-time dynamic and observation models are:

$$\mathbf{x}_k \sim p(\mathbf{x}_k | \mathbf{x}_{k-1}) \quad (1)$$

$$\mathbf{z}_k \sim p(\mathbf{z}_k | \mathbf{x}_k) \quad (2)$$

where  $\mathbf{x}_k$  represents the state of the dynamic system at time  $k$ ,  $\mathbf{z}_k$  is the observation vector, and  $p(\cdot)$  is a conditional probability density function.

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