

# Nonparametric Belief Propagation for Distributed Tracking of Robot Networks with Noisy Inter-Distance Measurements

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**Abstract**—We consider the problem of tracking multiple moving robots using noisy sensing of inter-robot and inter-beacon distances. Sensing is local: there are three fixed beacons at known locations, so distance and position estimates propagate across multiple robots. We show that the technique of Nonparametric Belief Propagation (NBP), a graph-based generalization of particle filtering, can address this problem and model multi-modal and ring-shaped uncertainty distributions. NBP provides the basis for distributed algorithms in which messages are exchanged between local neighbors. Generalizing previous approaches to localization in static sensor networks, we improve efficiency and accuracy by using a dynamics model for temporal tracking. We compare the NBP dynamic tracking algorithm with SMCL+R, a sequential Monte Carlo algorithm [1]. Whereas NBP currently requires more computation, it converges in more cases and provides estimates that are 3 to 4 times more accurate. NBP also facilitates probabilistic models of sensor accuracy and network connectivity.

## I. INTRODUCTION

Emerging advances in sensor networks: sensors, processors, and wireless communications are yielding improvements in sensor and transmission robustness, smaller sizes, cheaper devices, and lower power usage. Collaborative self-localization and tracking using wireless sensors has many applications such as tracking pallets in warehouses, vehicles on roadways, or firefighters burning buildings. In this paper we consider the problem of tracking multiple moving robots using noisy sensing of inter-robot and inter-beacon distances. Sensing is local: there are three fixed beacons at known locations, so distance and position estimates propagate across multiple robots.

Consider a graph where nodes correspond to beacons or mobile robots, and edges link pairs of nodes for which distance measurements are available. Robots may be multiple hops away from beacons. The inter-distance tracking problem is illustrated in Fig. 1. Inter-distance tracking is also closely related to simultaneous localization and mapping (SLAM) problems [2], in which each robot is treated as a uniquely identifiable, but mobile, landmark.

We formalize the inter-distance tracking problem using a probabilistic graphical model, which integrates prior estimates about beacon locations, sensor models, and robot

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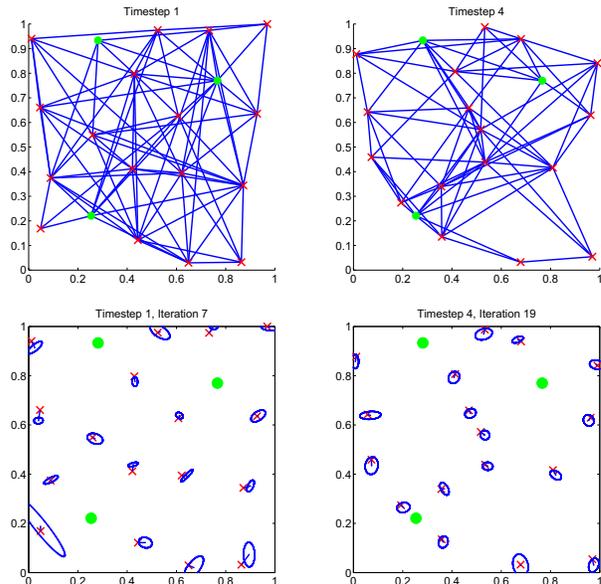


Fig. 1. Tracking seventeen robots at first and fourth timestep. The top figures depict inter-distance sensor connectivity: edges link pairs of robots that share a distance reading. Three green discs denote fixed reference beacons. True robot locations are indicated with red crosses. The bottom figures overlay true robot locations with point estimates of robot location generated by the NBP algorithm, shown as blue dots, at the center of blue ellipses, indicating twice the standard deviation. Note that although robots move substantially between timesteps and few robots are in direct contact with beacons, our inference shows good performance.

dynamics. In contrast with previous robot tracking methods, we then apply a variant of the belief propagation (BP) [3] algorithm, called nonparametric belief propagation (NBP) [4], to infer globally consistent estimates of robot location from noisy, local distance measurements using this graphical model. NBP approximates posterior distributions of unobserved variables by sets of representative samples. It is a generalization of particle filters [2] to domains with richer, non-temporal structure. NBP does not require linear or Gaussian models [5] and can model multi-modal and ring-shaped distributions produced by distance sensors.

The algorithm runs in two phases. Sec. V describes phase I, where we localize robots at the first timestep, using a similar formulation to the static localization algorithm of Ihler et al. [6]. Sec. VI describes phase II, where a dynamics model is used to combine inter-distance measurements over time.

Our tracking algorithm uses dynamics models to improve accuracy, while reducing computation and commu-