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Gaussian message passing-based cooperative localization on factor graph in wireless networks

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ABSTRACT

Location information has become attractive for a variety of applications in wireless networks. Cooperative localization was proposed to improve the performance in harsh environment where conventional localization methods failed due to the insufficient number of anchors. In this paper, distributed cooperative localization is studied based on message passing on factor graph. The joint *a posteriori* distribution of nodes' positions is represented by factor graph. Due to the nonlinearity between the positions and range measurement, the expressions of messages cannot be obtained in closed form by directly applying sum-product algorithm. Most existing methods resort to particle-based representation, which leads to both high computational complexity and large communication overhead. We propose to replace the factor node of the likelihood function by a linear Gaussian model. Accordingly, we are able to derive Gaussian messages on the revised factor graph, which only requires to update the mean vectors and the covariance matrices of multivariate Gaussian distributions. Simulation results show that the proposed method significantly outperforms the distributed maximum likelihood estimator and the extended Kalman filter, and performs very close to or even better than SPAWN estimator with much lower communication overhead and computational complexity in both static and mobile wireless networks.

1. Introduction

Location information has become an important feature in many wireless networks, and enabled a variety of applications, including navigation, tracking, monitoring, and emergency services [1]. Generally, the Global Positioning System (GPS) [2] is the most recognized technique for localization. However, localization using GPS may be failed in some harsh conditions, such as indoor environments, urban canyons, and tunnels. In addition, it can be costly and energy prohibitive to equip each device with a GPS receiver in some networks, especially in the large-scale wireless sensor networks [3]. Hence, only a few nodes called anchors in the networks have known positions, which will help the rest nodes called agents to be localized. Obviously, agents may fail to locate themselves due to the insufficient number of neighboring anchors available to them.

Recently, a location technique, namely, cooperative localization [4] has been introduced to enhance the conventional localization by enabling the cooperations among the agents through peer-to-peer communications. Each agent makes measurements with its neighboring nodes and exchanges information with them. The cooperative localization can work in harsh environment with insufficient anchors, which shows the advantage in sparse and limited-power networks, and

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improves the localization accuracy and reliability compared to the non-cooperative localization. Besides, the cooperative localization requires no additional infrastructure to be established, which makes it especially attractive in wireless ad hoc networks.

Many researches based on non-Bayesian estimators have been proposed for the range-based localization [5–10]. A least-squares method is proposed for the source localization in [5], where the iterative nonlinear methods, such as Newton–Raphson, Gauss-Newton and steepest descent, are used to tackle the nonlinear equation. However, these methods cannot guarantee the optimal results for the multimodal cost functions. In [6], linear least-squares method is proposed, which converts the nonlinear equation to linear one by introducing an additional variable. However, it suffers from the ill-conditioned measurement matrix when the distances between an agent and its neighbors are closely identical. In [7], the centralized maximum likelihood (ML) estimator is proposed to solve the relative location estimation in wireless sensor networks. The algorithm involves a multivariable nonlinear optimization problem that makes it difficult to implement in practice. To solve this problem, [8,9] relax the ML estimation to a centralized semi-definite programming problem and a distributed second-order cone programming problem, respectively. With these relaxations, localization problem becomes a convex optimization [11], which can be solved more efficiently.

All the above non-Bayesian estimators treat the positions of nodes to be located as unknown deterministic parameters and ignore their priors. However, the deterministic estimations of agents' positions by the non-Bayesian estimators cause the error accumulation when they act like anchors to help the neighboring agents in distributed cooperative localization, which leads to severe performance degradation. Therefore, the estimation uncertainties of agents' positions has to be considered when they act as reference nodes. To this end, Bayesian estimators [13–20] are utilized to locate the agents, which treat the nodes' positions as random variables. The extended Kalman filter (EKF) and unscented Kalman filter (UKF) [12] are proposed for cooperative localization in [13]. Both the EKF and UKF interpret the effects of neighbors' position uncertainties as range measurement errors, which leads to performance loss. In [14], the particle filter is proposed for cooperative localization in hybrid GNSS-terrestrial environment, which is especially useful for nonlinear systems at the cost of a huge computational complexity. Message passing algorithms are studied for the cooperative localization in [15–19], which are attractive for distributed processing. In [15], a nonparametric belief propagation (NBP) method is proposed for the self-localization in wireless sensor networks, which approximates messages by particles and the corresponding weights. However, the large numbers of particles leads to a huge computational complexity and large communication overhead. To reduce the communication overhead in NBP, a method using the approximations on the position beliefs by Gaussian mixtures and information censoring is proposed in [16]. In [17], a cooperative localization method based on the sum-product algorithm and factor graph [21] is proposed in wireless networks, which is named as SPAWN. However, directly applying SPAWN, especially computing messages on factor graph, becomes extremely difficult due to the nonlinearity between the positions and observations. Hence, approximations have to be made on the messages to ease the computational complexity. Note that, the message representations are closely related to the computational complexity and communication overhead in SPAWN, which has been studied in [18]. The particle-based method suffers both the high computational complexity and communication overhead, while the parametric method has a lower communication overhead, but may involve in parameters optimization by minimizing Kullback–Leilbler divergence [22], which may lead to a huge computational complexity using numerical methods. Variational message passing estimator is proposed for the self-localization of agents in wireless sensor networks in [19], which is a mean field solution to the estimation of the *a posteriori* distributions. However, the independence assumption of variables in the mean field solution tends to produce overly confident marginals [23].

In this paper, we consider two-dimensional Bayesian cooperative localization in wireless networks, which can be extended to the three-dimensional scenarios. Due to the nonlinearities between the positions and range measurements, localization has become a complex nonlinear and multivariate optimization problem. Hence, the linearization on the Euclidean norm in the range measurement is employed. Factor graph representation of the linearized state-space model is given. Then, the Gaussian messages are derived and passed on factor graph, which requires the mean vectors and covariance matrices of the multivariate Gaussian distributions to be updated and transmitted. Numerical results show that the proposed algorithm outperforms the distributed ML estimator and the extended Kalman filter. It performs very close to or even better than particle-based SPAWN with much lower computational complexity and communication overhead.

2. Problem formulation and system model

We consider a wireless network consisting of S anchors and M agents, where both the anchors and agents have position uncertainties. The position uncertainties of anchors are assumed to be smaller than that of agents at the beginning. All the nodes will update their position beliefs with the help of neighbors. Time is slotted. The two-dimensional location of node i at the kth slot can be denoted by $\mathbf{x}_i^{(k)} \triangleq [x_i^{(k)}, y_i^{(k)}]^T$, where T denotes the transpose. To obtain location information, each agent performs range measurements with its neighboring nodes, where the range measurement between the node j and i at the kth slot can be given as

$$z_{j\to i}^{(k)} = \|\mathbf{x}_j^{(k)} - \mathbf{x}_i^{(k)}\| + e_{j\to i}^{(k)}, \tag{1}$$

where $\|\cdot\|$ denotes the Euclidean norm and $e_{j\to i}^{(k)}$ is the range measurement error. Typically, $e_{j\to i}^{(k)}$ is Gaussian distributed with zero mean and variance $(\sigma_{j\to i}^{(k)})^2$ in the line-of-sight environment. Besides, messages can be exchanged among the nodes within the limited communication range.

Here, we define that the set notations of anchors and agents are $\mathcal{S}$ and $\mathcal{M}$, respectively. The neighboring anchors and agents of node i at the kth slot can be defined as $\mathcal{S}_i^{(k)}$ and