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Cooperative method for wireless sensor network localization

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ABSTRACT

In order to obtain an efficient wireless sensor network localization, several enhancements based on the decentralized approach are proposed. These features can be used in the cases when multiple distance measurements are used as input, where each node iteratively updates its estimated position using a maximum likelihood estimation method based on the previously estimated positions of its neighbors. Three novel features are introduced. First, a *backbone* is constructed, that is, a subset of nodes that are intermediaries between multiple beacon nodes, which guides the localization process of the other (non-backbone) nodes. Second, the space is perturbed more often during the earlier time steps to avoid reaching poor local minima in some cases regarding the localization optimization function. Third, for better localization of the non-backbone (or peripheral) nodes and avoidance of the rigidity problem, 2-hop neighboring distances are approximated. The introduced features are incorporated in a range-based algorithm that is fully distributed, shows good performance, and is scalable to arbitrary network size.

1. Introduction

Wireless sensor networks (WSNs) have recently attracted considerable research interest by providing unprecedented opportunities for monitoring and controlling homes, cities, and the environment. They consist of spatially distributed smart autonomous sensors, networked through wireless links and deployed in large numbers. Self-localization capability is a highly desirable characteristic of wireless sensor networks. Sensor network localization algorithms estimate the locations of sensors with initially unknown location information by using knowledge of the positions of a few sensors and inter-sensor measurements such as distance and bearing measurements. Sensors with known location information are called beacons or anchors and their locations can be obtained by using a global positioning system (GPS), or by installing them at points with known coordinates.

Many approaches for WSN localization have been studied in the literature. Overviews of WSN localization techniques are presented in [1–4]. For a survey of localization in mobile WSNs, we refer to [5]. The spatio-temporal cooperation for localization and navigation is extensively studied in [6,7].

1.1. Previous work

Localization techniques can be broadly classified into two categories: range-based and range-free. In large-scale WSNs, where signal range is limited, range-based schemes typically require a lot of beacon nodes to produce accurate results. On the other hand, range-free schemes estimate

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inter-node distances based on hop count information, thus all target nodes can be localized with fewer beacon nodes. Range-free techniques are those where node position estimation is not based on the distance estimation between nodes but on the solution to heuristic or optimization problems with a decentralized characteristic. The typical range-free algorithms include Centroid [8], CPE (Convex Position Estimation) [9], and DV-hop (Distance Vector-hop) [10]. Centroid and CPE are simple, having low complexity, but they require a normal node to have at least three neighboring beacons. DV-hop algorithm can handle the case where a normal node has less than three neighbor beacons.

Since the quality of localization is easily affected by node density and network conditions, range-free approaches typically provide imprecise estimation of node locations. Range-based approaches measure the Euclidean distances among the nodes with certain ranging techniques and locate the nodes using geometric methods, such as time of arrival (TOA), time difference of arrival (TDOA), and angle of arrival (AOA).

Here we focus on range-based designs for sparse networks. Several range-based algorithms that address the network or beacon sparseness problem will be first reviewed. Savarese et al. [11] proposed a virtual-coordinate-based algorithm TERRAIN to address the sparse beacon problem. The algorithm constructs a virtual coordinate system on each beacon and takes the advantage of the property that the virtual coordinate holds the distance information between each node pair.

Other researchers utilized local maps to localize non-beacon nodes [12,13]. They first use distance measurements between neighboring nodes to construct local maps, and then stitch them together to form a global map. Savvides et al. [14] used collaborative multilateration among neighbors to compensate the ranging information shortage, which localizes nodes by forming an over determined system of equations with a unique solution set. Collaborative multilateration performs better than trilateration in sparse networks. The disadvantage is that the collaboration is restricted in neighbors, so that the performance gain is limited.

Goldenberg et al. [15] introduced the concept of finite localization, which holds all candidate positions of each node and prunes incompatible ones when other nodes join the procedure. Given proper beacon distribution, the algorithm is able to locate nodes in a globally rigid region, but may fail to localize the regions that contain few beacons. Wang et al [16] introduced the concept of component, by which nodes are grouped into components which are able to better share ranging and beacon knowledge. Operating on the granularity of components, the proposed design relaxes two essential restrictions in localization: the node ordering and the beacon distribution. Zhao et al [17] proposed a combined and differentiated localization approach for localization that exploits the strength of range-free approaches and range-based approaches using received signal strength indicator (RSSI). To achieve a better ranging quality, the proposed algorithm incorporates virtual-hop localization, local filtration, and ranging-quality aware calibration.

The cooperation between the network nodes, i.e., the exchange of messages, can be employed for different purposes. Depending on which nodes are used as reference points for each individual location estimation, the cooperative localization methods can be classified in two main classes. Multi-hop localization methods, such as the aforementioned ones, use the beacon nodes as individual reference points. There the cooperation takes place primarily to estimate the distances between the non-beacon nodes and the beacons, often located multiple hops away. Later, these distances are used for calculating individual position estimates by methods such as multilateration for example. On the other hand, methods such as [6,18] and the one described in this paper perform iterative update of the position estimate of every node by using the position estimates of its neighbors as reference points.

Sensor network localization is a nonconvex optimization problem that, however, can be converted to a Semi-Definite Programming (SDP) problem by transforming the quadratic embedding constraints to a matrix inequality, which can be finally rewritten as a standard SDP problem. This approach has recently attracted considerable attention; for example, a technique for localization of sensors based on considering together local structures that are fit together in an as-rigid-as-possible manner is proposed recently in [19]. The local structures consist of reference patches (set of four sensors) and reference triangles, both obtained from inter-sensor distances.

In [20] the authors focused on the problem of sensor network localization in the plane by considering the group of algorithms that integrate local distance information (patches) into a global structure determination. Each patch is separately localized in a coordinate system of its own using either the stress minimization approach or by SDP. To every patch there corresponds an element of the Euclidean group Euc(2) of rigid transformations in the plane, and the goal is to estimate the group elements that will properly align all the patches in a globally consistent way. In [21], Shamsi and co-workers analyzed and determined sufficient conditions and formulations that guarantee that the SDP relaxation is exact, i.e., give the correct solution of the sensor localization problem. These conditions can be useful for designing sensor networks and managing connectivities in practice.

1.2. Our contribution

In this paper, we focus on introducing new features that will improve the performances of decentralized algorithms for localization that do not use centralized units for computation and data gathering. The localization process, however, is based on known global positions of some of the network nodes. These are necessary for identifying the absolute positions of the other nodes. Iterative position estimation update is executed by each node using the approximated distances from its neighbors. Hence, the marginal distribution of each node is optimized since the nodes' locations are the component variables comprising the joint distribution that describes the state space. However, optimizing the marginal distributions, as convenient as it is, does not always optimize the joint distribution. The aim of