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Wireless sensor networks localization based on graph embedding with polynomial mapping☆

Hao Xu[a], Huafei Sun[a,*], Yongqiang Cheng[b], Hao Liu[c]

[a] School of Mathematics and Statistics, Beijing Institute of Technology, Beijing (100081), China
[b] School of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan (410000), China
[c] School of Science, University of Science and Technology Liaoning, Anshan (114051), China

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ABSTRACT

Localization of unknown nodes in wireless sensor networks, especially for new coming nodes, is an important area and attracts considerable research interests because many applications need to locate the source of incoming measurements as precise as possible. In this paper, in order to estimate the geographic locations of nodes in the wireless sensor networks where most sensors are without an effective self-positioning functionality, a new graph embedding method is presented based on polynomial mapping. The algorithm is used to compute an explicit subspace mapping function between the signal space and the physical space by a small amount of labeled data and a large amount of unlabeled data. To alleviate the inaccurate measurement in the complicated environment and obtain the high dimensional localization data, we view the wireless sensor nodes as a group of distributed devices and use the geodesic distance to measure the dissimilarity between every two sensor nodes. Then employing the polynomial mapping algorithm, the relative locations of sensor nodes are determined and aligned to physical locations by using coordinate transformation with sufficient anchors. In addition, the physical location of a new coming unknown node is easily obtained by the sparse preserving ability of the polynomial embedding manifold. At last, compared with several existing approaches, the performances of the presented algorithm are analyzed under various network topology, communication range and signal noise. The simulation results show the high efficiency of the proposed algorithm in terms of location estimation error.

1. Introduction

Wireless sensor networks (WSN) have received extensive interest lately as a promising technology in many applications of wireless communications, containing manufacturing [1], health caring [2], environment monitoring and forecasting [3], habitat monitoring and tracking. The location of nodes in WSNs plays an important role in most application fields. In addition, knowing the relative locations of sensors makes use of location-based addressing and routing protocols, which can improve network robustness and energy-efficiency effectively. Therefore, sensor nodes localization is one of the fundamental issues in the implementation of WSNs. In the large scale of sensor networks, even though some sensor nodes could be equipped with a global positioning system(GPS) to provide them with their absolute position, this is currently a costly solution or impossible solution to some indoor cases. Therefore, it is often assumed that the positions of some nodes are known exactly, so that it is possible to find the absolute positions of the remaining nodes in the WSNs through the known locations of sensor nodes and the measurement data. The main task of WSNs localization algorithm is to determine the positions of sensor nodes in a network given incomplete and disturbed by noise. Locating the unknown nodes in a wireless system involves the collection of location information from radio signals traveling between the unknown nodes and a number of reference anchor nodes(anchors). There are many classical positioning techniques, including the angle of arrival(AOA) [4–6], the received signal strength(RSS) [7–9], or time of arrival(TOA) [10–12], which can be all used to determine the location of unknown nodes. The AOA technique uses the angles between the unknown node and a number of anchors to estimate the location of the unknown nodes, the RSS estimates the received signal strength, and the time-based approaches measure the arrival time of the received signal, respectively.

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* Corresponding author.
E-mail addresses: xhheqiao@126.com (H. Xu), huafeisun@bit.edu.cn (H. Sun), nudtyqcheng@gmail.com (Y. Cheng), liuhao123@ustl.edu.cn (H. Liu).

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Though many traditional localization methods can reach a high localization accuracy, they are not suitable for dealing with large scale sensor networks due to lot of time and material cost. Recently, in order to handle these noisy measurements and time consumption, several algorithms making use of kernel-based machine learning have been proposed for locating sensor nodes with inaccurate measurement in WSNs. Some different measurement methods about the sensor communication with each other are presented in [7]. A graph embedding localization algorithm for WSNs is introduced in [13], which views the sensor nodes as a group of distributed devices to construct a graph to preserve the topological structure of the sensor networks, and employs an appropriate kernel function to measure the dissimilarity between sensors. A kernel isometric mapping(KIsomap) algorithm is used to determine the relative locations of sensors based on geodesic distance [14] and a semi-supervised Laplacian regularized least squares algorithm is presented in [15] using the alignment criterion to learn an appropriate kernel function. In addition, a semi-supervised manifold learning is used to estimate the location of mobile nodes in the WSNs [16].

Most kernel-based localization algorithms can capture the nonlinearity of the measured data due to the nonlinear property of the kernel function. However, they cannot deal with the sensibility of measurement parameters. In order to overcome the shortcoming of the sensitive to the neighborhood parameters, a robust localization method with ensemble-based manifold learning is introduced in [17], and a local patches alignment embedding localization is proposed in [18]. However, a main drawback of many manifold learning methods is that they learn the low-dimensional output data samples implicitly. We cannot obtain an explicit mapping relationship from the input data manifold to the output embedding after the training process. Therefore, in order to obtain the physical locations of new coming samples, the learning procedure has to be extremely time consuming for sequentially arrived localization data. Although some methods based on linear projection have been proposed to get an explicit mapping, the linearity assumption may still be too restrictive. Meanwhile, the kernel embedding methods have been also proposed to give nonlinear but implicit mappings for manifold learning localization [19–21]. In addition, because these mappings are computed within a subset of the feature space rather than the whole feature space itself and are given in terms of the kernel and the training data samples explicitly, their computational process would be quite complicated for large-scaled sensor networks.

In this paper, a new graph embedding algorithm with polynomial mapping (GEPM) is proposed for locating unknown nodes in WSNs, especially to the new coming nodes. Firstly, location data based on pair-wise distance is obtained by the geodesic distance measurement. Consequently, in order to solve the problem of the sparse structure of the sensor networks and the sensitive to neighborhood parameters easily, we can construct a graph to represent the topological structure of the sensor networks and calculate the weight matrix and the sparse preserving matrix. And then, an eigenvalue function can be obtained by the polynomial mapping based on spectral embedding optimization problem. Letting some eigenvectors corresponding to the smallest eigenvalues of function be the polynomial coefficients, the relative locations of all sensor nodes can be obtained based on Rayleigh-Ritz theorem. At last, by the coordinate transformation, we can get final physical locations of all unknown nodes. Meanwhile, for the new coming unknown nodes, we can easily obtain the geodesic distance between them with the datum nodes. Based on the graph theorem, the relative coordinates and physical coordinates can be calculated simply. Compared with linear projection methods and kernel-based nonlinear mapping methods, the presented algorithm gives more accurate embedding and out-of-sample extension results and, meanwhile, is very fast in locating new coming samples.

The main features of the proposed locating method are given as follows.

- The geodesic distance matrix is used to construct the neighbor graph of the WSNs, which reduces the influence of noise in the measurement and receives high accurate location estimation, even with error-prone distance information. In addition, the datum nodes are selected to determine the geodesic distance vector, i.e., the high dimensional localization data, based on the geodesic distance matrix. Comparing with some previous manifold learning localization methods, it is to further reduce the computational complexity and enhance the precision of the solution in our approach. The detailed analysis is given in Section 4.4.
- The embedding mapping is nonlinear and the high dimensional data space is considered as a nonlinear manifold. Comparing with the linear projection-based methods, the proposed mapping provides a nonlinear polynomial mapping from the high dimensional localization data space to the low dimensional representation space. Therefore, it is more reasonable to use a polynomial mapping to handle data samples lying on nonlinear manifolds. Meanwhile, the proposed localization method is suitable to the large scale WSNs and has high localization accuracy.
- The mapping can be straightforward to locate any new sensor nodes participating the WSNs. It is different from the traditional manifold learning localization methods such as MDS, SDP, SVM, and ISOMAP, which are not clear how new localization data sample can be embedded in the low dimensional space for the implicit mapping. Meanwhile, in contrast to the explicit manifold learning algorithm such as KLPP and S^2LapRLS, the proposed localization method has a lower computational complexity and is fast and efficient in finding the low dimensional representations of new localization data even for vary lager data sets.
- The influence of the datum nodes to the localization accuracy is analyzed in detail based on the RMS error under different anchors, communication range and noise standard deviation for WSNs. Finally, the optimal selection of the datum nodes is first given by $m_{op} = [-\frac{3}{2} + \sqrt{2N + \frac{9}{4}}]$ with $q = 2$ for different sensor nodes and interested localization area. The detailed analysis and experiments are given in Section 4.1.

The rest of this paper is organized as follows. The localization problems, containing graph construction, original nodes location and new coming data calculation, are presented in Section 2. Section 3 presents the main contribution of this paper about the sensor nodes location estimation algorithm based on the graph embedding theorem with polynomial mapping. The extensive simulation results are described in Section 4. Finally, some concluding remarks and future works are given in Section 5.

2. Localization problem statement

Let us consider a p-dimensional(pD) localization problem in WSNs consisting of N sensor nodes in an interesting area $C \subseteq \mathcal{R}^p (p = 2 \text{ or } 3)$. Without loss of generality, we assume that the first n sensors are anchors, and the rests are unknown nodes. At the same time, we select the first $m(p < m)$ sensor nodes as datum nodes. The locations of anchors can be obtained by location equipments, e.g., global positioning system, while the unknown nodes need to be measured by the anchors and localization data. Let $\mathbf{p}_i$ be the ith sensor node whose coordinate is expressed as $(\mathbf{p}_{1i}, \ldots, \mathbf{p}_{pi})^T, i = 1, 2, \ldots, N$, and every sensor node can transmit