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Distributed on-line multidimensional scaling for self-localization in wireless sensor networks

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ABSTRACT

The present work considers the localization problem in wireless sensor networks formed by fixed nodes. Each node seeks to estimate its own position based on noisy measurements of the relative distance to other nodes. In a centralized batch mode, positions can be retrieved (up to a rigid transformation) by applying an eigenvalue decomposition on a so-called similarity matrix built from the relative distances. In this paper, we propose a distributed on-line algorithm allowing each node to estimate its own position based on limited exchange of information in the network. Our framework encompasses the case of sporadic measurements and random transmissions. We prove the consistency of our algorithm in the case of fixed sensors. Finally, we provide numerical and experimental results from both simulated and real data. Simulations issued to real data are conducted on a wireless sensor network testbed.

1. Introduction

The problem of self-localization involving low-cost radio devices in WSN can be viewed as an example of the internet of things (IoT). The evolution in the last 50 years of the embedded systems and smart grids has contributed to enable the wireless sensor networks (WSNs) integrate the emerging system of the IoT. Recently, advanced applications to handle specific tasks require the support of networking features to design cloud-based architectures involving sensor nodes, computers and other remote component. Among the large range of applications, location services can be provided by small devices carried by persons or deployed in a given area, *e.g.* routing and querying purposes, environmental monitoring, home automation services.

In this paper we investigate the problem of localization in WSNs. We assume that wireless sensor devices are able to obtain received signal strength indicator (RSSI) measurements that can be related to a ranging model depending on the inter-sensor distances. The multidimensional scaling mapping method (MDS-MAP) consists in applying eigenvalue decomposition to a so-called similarity matrix constructed from the squared inter-sensor distances. Then, the sensors' positions can be recovered (up to a rigid transformation) from the principal components of the similarity matrix [1,2]. As opposed to time difference of arrival (TDOA) and angle of arrival (AOA) techniques, the MDS-MAP approach allows us to recover the network configuration based on the sole RSSI, and can be used without any additional hardware or/and synchronization specifically devote to self-localization.

MDS-MAP has been extensively studied in the literature [2–6]. The algorithm is generally implemented in a centralized fashion. This requires the presence of a fusion center which gathers sensors' measurements, computes the similarity matrix, performs the eigenvalue decomposition, and

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eventually sends the positions to the respective sensors. In this paper, we provide a fully *distributed* algorithm which do not require RSSI measurements to be shared. In addition, our algorithm can be used *on-line*. By on-line, we mean that the current estimates of the sensors' positions are updated each time new RSSI measurements are performed, as opposed to batch methods which assume that measurements are collected *prior* to the localization step. Therefore, although we assume throughout the paper that the sensors' positions are fixed, our algorithm has the potential to be generalized to moving sensors, with aim to track positions while sensors are moving.

The paper is organized as follows. In Section 2, we provide the network and the observation models. We also provide a brief overview of standard self-localization techniques for WSN. Section 3 presents the centralized version of the MDS-MAP algorithm. The proposed distributed MDS-MAP algorithm is provided in Section 4. An additional refinement phase is also proposed in Section 5 where our MDS-MAP algorithm is coupled with a distributed maximum-likelihood estimator. In Section 6, numerical experiments based on both simulated and real data are provided. Section 7 gives some concluding remarks.

2. The framework

2.1. Network model

Consider N agents (*e.g.* sensor nodes or other electronic devices) seeking to estimate their respective positions defined as $\{\boldsymbol{z}_1, \ldots, \boldsymbol{z}_N\}$ where for any i, $\boldsymbol{z}_i \in \mathbb{R}^p$ with $p=2$ or 3. We assume that agents have only access to noisy measurements of their relative RSSI values. More precisely, each agent i observes some RSSI measurements $P_{i,j}$ associated with other agents $j \neq i$. Here, $P_{i,j}$ is a random function of the Euclidean distance $d_{i,j} = \| \boldsymbol{z}_i - \boldsymbol{z}_j \|$ between nodes i and j. The statistical model relating RSSI values to inter-sensor distances is provided in the next paragraph.

The goal is to design a distributed and on-line algorithm to enable each sensor node to estimate its position $\boldsymbol{z}_i$ from noisy measurements of the distances. Before going further in the description of the RSSI statistical model, it is worth noting that the localization problem is in fact ill-posed. Since the only input data are distances, exact positions are identifiable only up to a rigid transformation. Indeed, quantities $(d_{i,j})_{\forall i,j}$ are preserved when an isometry is applied to the agents' positions, *i.e.*, rotation and translation. The problem is generally circumvented by assuming a minimum number of *anchors* or also named *landmarks* (sensor nodes whose GPS-positions are known), *e.g.* $M=3$ or 4 when $p=2$, and considering these prior knowledge to identify the indeterminacy. This point is further discussed in Section 2.3.

2.2. Received signal model

We rely on the so-called log-normal shadowing model (LNSM) to model RSSI measurements as a function of the inter-sensor distance [7]. We define the average path loss $\mathrm{PL}(d)$ at a distance d expressed in dB as $\mathrm{PL}(d) = \mathrm{PL}_0 + 10\eta \log_{10}\frac{d}{d_0}$, where the parameters η, d_0 and PL_0 depend on the environment (see Section 6). Given that the distance between sensors i and j is $d_{i,j}$, we define the RSSI between i and j as a random variable $P_{i,j}$ satisfying

$$P_{i,j} = -\mathrm{PL}(d_{i,j}) + \epsilon_{i,j} \tag{1}$$

where $(\epsilon_{i,j}: i \neq j)$ are thermal noises assumed independent with zero mean and variance σ^2. Assume that a given agent i is provided with T independent copies $P_{i,j}(1), \ldots, P_{i,j}(T)$ of the random variable $P_{i,j}$ and let $\bar{P}_{i,j} = T^{-1}\sum_{t=1}^{T} P_{i,j}(t)$ be the empirical average. An unbiased estimate of the squared distance $d_{i,j}^2$ is given by

$$D(i,j) = d_0^2 \frac{10^{(-\bar{P}_{i,j} - \mathrm{PL}_0)/5\eta}}{C^4} \tag{2}$$

where $C = 10^{\sigma^2 \ln 10/2T(10\eta)^2}$ (see for instance [8]). Indeed, it can be easily checked that the mean and the variance of the unbiased estimator (2) are respectively $\mathbb{E}[D(i,j)] = d_{i,j}^2$ and $\mathbb{E}[(D(i,j) - d_{i,j}^2)^2] = d_{i,j}^4(C^8 - 1)$. The construction of unbiased estimates of squared distance will be the basic ingredient of our distributed MDS-MAP algorithm.

2.3. Overview of some localization techniques

Several overview papers have been published in the last ten years dealing with the classification of the localization techniques (see [9] or [10]). In some situations, localization is made easier by the presence of *anchor* nodes whose positions are assumed perfectly known. Other methods, called anchor-free, do not require the presence of such landmarks.

Classical anchor-based methods involve the resolution of a single unknown position of a sensor node at a time by means of RSSI values following the LNSM coming from a fixed number of surrounding anchor nodes or landmarks. Since the sensor node only uses the information from known positions, its position can be expressed in absolute coordinates, *i.e.*, anchor positions in GPS-coordinates. When considering a noisy scenario, several works coupled the classical methods (*trilateration*, *multilateration* [11] or *min–max* [12]) with a least squares problem. In particular, [12–14] and more recently [15] consider multi-hop communications between the sensor nodes by following a sequential approach. In sequential approaches, the estimation process is started by a well-chosen node, *e.g* in [15] the connectivity of all sensors is previously known, then information is aggregated and the process is repeated by a following node chosen according to some criteria, *i.e.*, proximity to anchor nodes. Other approaches focus on the statistical distribution of the received RSSI measurements coming from the landmarks. The goal is to consider a parametric model for the received signal and to apply maximum likelihood estimator (MLE). Most works consider the LNSM (see for instance [16] or [17]) while others assume alternative statistical models (see [18] or [19]).

When no anchor is available, the configuration of the network can still be recovered on a relative coordinate system instead of the GPS absolute coordinate system. When distances between nodes are view as similarity metrics, the positioning problem is referred to multidimensional scaling (MDS). The aim is to find an embedding from the N nodes such that distances are preserved. In classical MDS [1,