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Distributed adaptive direct position determination of emitters in sensor networks

Wei Xia [a,b,*], Wei Liu [a]

[a] School of Electronic Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan 611731, PR China
[b] Department of Electrical and Computer Engineering, Stevens Institute of Technology, Hoboken, NJ 07030, USA

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A B S T R A C T

In the conventional centralized adaptive direct position determination (C-ADPD) approach, the emitter position is estimated at the fusion center (usually one of the sensors) with all the available signal samples transmitted from different sensors. This centralized framework may be not suitable for large-scale sensor networks due to the computational capability and energy storage bottleneck of the single fusion center. Furthermore, transmitting all the received signals to the fusion center usually needs multi-hop transmission, which is a big challenge to the communication bandwidth of the sensor networks. In this paper, we propose a fully distributed adaptive direct position determination (D-ADPD) approach for emitter localization. Without a dedicated fusion center in this distributed framework, signal samples received by sensors are transmitted to their corresponding neighbors with single-hop transmission only; the communication cost could be significantly reduced. Every sensor in the network locally estimates the common emitter position with an adaptive algorithm by fusing its information with diffused parameter estimates from its neighbors; the computational complexity is distributed among each sensor. Simulation results validate the improved convergence and steady-state performance of the proposed approach with enhanced elasticity and robustness in different scenarios.

1. Introduction

Passive localization for radio emitters is one of the essential topics in signal processing and has already been applied in many practical engineering fields, such as radars, sonars, Wireless Sensor Networks (WSNs) and so on.

One of the most common techniques of passive localization is based on the Time Difference Of Arrival (TDOA). Classical methods use two steps to accomplish the emitter localization. First, the TDOAs are obtained from pairs of the received signals among sensors by time delay estimation algorithms, such as generalized correlation method [1], adaptive time delay methods [2–4], etc. Second, the emitter position is estimated by making use of the TDOAs through localization algorithms, for example, Taylor series expansion method [5], two-step weighted least square approach [6], constrained weighted least squares algorithm [7], approximate maximum likelihood localization algorithm [8] and semi-definite programming method [9].

Since the two-step methods generally ignore the fact that all the TDOA measurements must be consistent to a common emitter in the first step, they are suboptimal. By noticing this, Weiss and Bar-Shalom recently proposed the Direct Position Determination (DPD) algorithm by introducing the underwater matching field theory to emitter localization field [10–13]. Based on the Maximum-

* Corresponding author at: School of Electronic Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan 611731, PR China.
E-mail address: wx@uestc.edu.cn (W. Xia).

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Likelihood (ML) criterion, the emitter position could be estimated in a single step with the received signals directly without extracting the TDOAs/FDOAs (Frequency Differences Of Arrival) [12]. More recently, based on the Minimum Mean Square Error (MMSE) criterion, an adaptive DPD (ADPD) algorithm has been proposed [14,15]. The ADPD algorithm is more suitable in time-varying environments due to its inherent tracking ability, compared to the original ML-DPD algorithm. It has been demonstrated that, compared with the conventional two-step approaches, both the ML-DPD and ADPD algorithms could obtain improved localization accuracy by considering the constraint that all TDOA measurements must be consistent to a common emitter.

It should be noted that, however, both the ML-DPD and ADPD algorithms are centralized with signals received at each sensor transmitted to the sole fusion center, which is usually one of the sensors. Multi-hop transmission is usually needed in this data transfer model, which incurs an expensive cost of the network communication bandwidth, not to mention the possible link failure and security problems. With limited communication resources, the centralized framework may be not easily implemented. Additionally, since the emitter position is estimated in the sole fusion center with the signal samples received by other sensors, the centralized localization system might result in estimate deterioration with one or more sensors experience severe signal propagation fading. As validated by the simulations further ahead, the centralized ADPD localization system is vulnerable especially when the fusion center unexpectedly breaks down. Furthermore, it would also be a big challenge of manipulating a great number of sensors in the network with limited computation capability and energy consumption.

Aiming at alleviating these faults of the centralized direct position determination algorithms, we herein propose a fully Distributed Adaptive Direct Position Determination (D-ADPD) approach with a novel *global* objective function. Hence, the D-ADPD approach, with the following merits, may be regarded as a nontrivial extension of the centralized ADPD (C-ADPD) algorithm [14].

First, in the proposed distributed method, the signal samples received by each sensor are only transmitted to its neighboring sensors with a single-hop, instead of being transmitted to the fusion center. Hence, multi-hop transmission is completely avoided. The possible data loss during the multi-hop transmission would be reduced as well.

Second, the exactly same localization algorithm (with different inputs) are executed in each sensor in the proposed distributed framework, and the common emitter position are locally estimated in every sensor simultaneously. This makes the distributed localization system more robust when some of the sensors experience significant signal propagation fading, or even break down; either case would be devastating for the single fusion center in the centralized algorithm.

Third, in the centralized framework, the computational load and energy consumption of the single processor would be inevitably increased with the growing of the number of sensors in the sensor network. By contrast, in the proposed distributed framework, either the computational load or energy consumption is distributed to every sensor rather than burdened by one single sensor. Moreover, the computational load and energy consumption on each sensor is only proportional to the number of its neighboring sensors rather than the total number of sensors in the network. Hence, the largest computational load and energy consumption in each sensor is totally controllable with the largest number of neighboring sensors of each sensor restricted.

Furthermore, as the proposed distributed localization approach is a nontrivial extension of the diffusion LMS algorithm, the communication load in the networks may be reduced by allowing each senor to receive the intermediate estimates from only a subset of its neighbors at each iteration, as indicated by the reduced-communication diffusion LMS scheme [16], or using the dynamic diffusion LMS algorithm by sharing reliable information only with the neighbors [17].

There are also some related works on distributed localization. Pourhomayoun and Fowler [18] proposed an approximate DPD algorithm by applying Gershgorin's theorem. Although this distributed method could reduce the computational load on each sensor, the communication cost is very huge, which may not be suitable for large-scale sensor networks. Furthermore, it is not an adaptive approach, which would not be applicable in time-varying environments. Another work we would like to mention is the diffusion LMS based localization algorithm [19]. It is adaptive with good mobile tracking ability, but it is a two-step method, in which the received signals strength (RSS) and the signal propagation time must be estimated in a preliminary step. In [20], another RSS based localization algorithm utilizing incremental subgradient optimization methods is proposed. However, this incremental strategy needs the estimate to be cycled through the network, which is not robust when some of the sensors in the cycle path break down. Moreover, finding out a cycle path in the network is an NP hard problem. In [21], the localization problem based on RSS is formulated as the intersection computation of a group of sensing rings, and is converted into two weighted convex optimization problems. A distributed alternating projection-based algorithm is proposed to solve the localization problem. Related projection-based localization approaches may be also found therein [21]. In [22], a Maximum Likelihood Estimator (MLE) for two-way Time-Of-Arrival (TOA)/TDOA positioning has been proposed. Utilizing the orthogonal Projection Onto Convex Sets (POCS) approach, the estimator is robust and can be implemented in a distributed manner. Lindgren et al. [23] considered the estimation of the motion of a passing acoustic source from the observed Doppler shift by Gauss–Newton variable projection techniques, and briefly addressed the corresponding network distributed estimation method. However, the methods in [22] and [23] are neither one-step nor diffusion based algorithms. Hence, our proposed distributed approach is distinguished from all the aforementioned algorithms.

The main contributions of this work is summarized as follows.