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Bi-iterative algorithm for joint localization and time synchronization in wireless sensor networks

Qiang Tian, Da-Zheng Feng*, Hao-Shuang Hu, Fan Yang, Lei Wei

National Laboratory of Radar Signal Processing, Xidian University, Xi'an 710071, China

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This paper efficiently solves the problem of joint localization and synchronization in wireless sensor networks by using two-way message exchange mechanism. Employing an affine model of unsynchronized local clocks, we first establish the famous Maximum Likelihood (ML) estimator for joint localization and synchronization, which derives the best consistent solution. Unfortunately, achieving directly the ML estimator is usually difficult because the ML cost functions are highly non-linear and non-convex. In order to effectively obtain the ML estimator, a novel bi-iterative algorithm is proposed by alternately searching the sensor node location and clock parameters (clock skew and clock offset). We prove that the proposed algorithm is convergent, and analyze that its estimation accuracy for the sensor node locations and clock parameters can approximately reach the Cramer–Rao Lower Bound (CRLB) under the mild noise condition. Compared with some previous methods, the proposed bi-iterative algorithm is more computationally efficient, and takes fewer anchor nodes and less communication overhead. Simulation results verify theoretical analysis and show that the proposed algorithm has the better performance than the several existing algorithms.

1. Introduction

Wireless Sensor Networks (WSNs) have been widely applied in target detection, monitoring, tracking, control and other fields, due to their flexibility, multi-functionality and attractive performance [1]. Localization and time synchronization are usually the two key factors for WSNs to realize their application functionalities. On the one hand, the location information of sensor nodes in WSNs must be known in order to make the collected measurements meaningful [2]. On the other hand, time synchronization provides a common time frame to different sensor nodes in WSNs, which is necessary for many fundamental operations such as data fusion, power management and transmission scheduling [3].

Since localization is a key technology in WSNs, it has been a hot research topic for a long time. In most cases, the positions of the sensor nodes can be obtained based on Global Positioning System (GPS) [4]. However, GPS-based localization methods are not always suitable for WSNs because of the constraints on the hardware cost, size and energy consumption of sensors. What's worse is that the GPS may be unavailable in some special environment, such as indoors and underground. Typically, some anchors with the known positions are used for localizing a sensor node in WSNs. These anchors measure or estimate the positioning signals and the source node locations are cooperatively searched by geometric methods. The commonly used positioning signals include Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA), Received Signal Strength (RSS), Frequency Difference of Arrival (FDOA) for a moving target [5–12]. However, it is worth mentioning that finding a source position is a non-trivial task because a node position is nonlinearly related to the positioning signals. For more detailed information about localization techniques, interested readers are referred to [13] and the references therein.

Since different sensors use different hardware to produce time clocks, their local clocks are not synchronized with each other. This often causes difficulties to interpret, integrate and exploit the data collected by different sensor nodes. Various time synchronization schemes specifically designed for WSNs have been established in some literatures, including Flooding Time Synchronization Protocol (FTSP) [14], Timing-Sync Protocol for Sensor Networks (TPSN) [15], Reference Broadcast Synchronization (RBS) [16] and Time Diffusion Synchronization Protocol (TDP) [17]. These schemes are mainly researched from protocol design point of view. Recently, some papers investigated the synchronization problem in the signal processing framework and developed some algorithms based on the two-way message exchange mechanism [18,19].

As mentioned before, both localization and synchronization have been often treated as two independent problems. However,

* Corresponding author.
E-mail address: dzfeng@xidian.edu.cn (D.-Z. Feng).

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in WSNs, they are closely related and share many common information. For example, the two problems can be solved by the same noisy measurements observed by the same anchor nodes. Especially, in practical applications, the performance of localization methods based on the measured time (such as TOA, TDOA) strongly depends on time synchronization accuracy among the sensor nodes [2,20]. It has been shown that jointly estimating synchronization and localization can significantly improve the performance than estimating separately [21–23]. The main reason of good performance is that, in the joint approaches, the clock parameters and source node location are estimated simultaneously by exploiting the close relationship and mutual information between the two problems.

From statistical signal processing point of view, the joint localization and synchronization problem is essentially a parameters estimation [3,23]. The Maximum Likelihood (ML) estimator for joint synchronization and localization is firstly derived in [23]. The ML estimator can provide the optimal accuracy asymptotically [24,25]. However, the cost function of the ML estimator is highly nonlinear and nonconvex, and may be hard solved. To obtain the solution of the ML estimator, several algorithms have been proposed in the published papers, and they can broadly be classified into three categories. In the first category, the ML estimator is solved by iterative approaches such as the Taylor-series algorithm [26]. However, the iterative methods may diverge in the presence of large measurement noise level, especially when a good solution initialization is unavailable. Moreover, the iterative methods have high computation complexity since they simultaneously compute the location and clock parameters (clock skew and clock offset) of the source node in each iteration. In the second category, the original joint problem is linearized via linear approximation techniques. Zheng and Wu [23] developed a well-known Constrained Weighted Least Square (CWLS) algorithm by introducing three intermediate variables, which can get the solution close to the CRLB in certain scenario. Afterwards, some other linear approximation approaches are further proposed in [27,28]. Although each of these linear approximation algorithms has closed-form solution, their performances are relatively poor when the measurement-noise level is high. In the third category, the ML problem is converted into a convex one (Semi-Definite Programming, SDP) by convex relaxation approaches [29,30]. The SDP-based methods can guarantee the global convergence without requiring any initialization [31,32]. However, their two obvious defects are as follows. First, computational complexity of the SDP-based methods is higher than that of a linear estimator. Second, they are sub-optimal in most cases because the relaxation operations cause the performance loss [32]. In addition to these conventional algorithms, some new techniques, such as approximation-based neural networks [33,34] and fuzzy schemes [35,36] are widely discussed in different systems to deal with the nonlinear problems. These methods can be used for references to solve the joint problem.

In summary, most aforementioned estimators are approximations of the joint localization and synchronization problem. Their performances are relatively poor under the condition of high measurement noise level, fewer anchor nodes and less message exchanges. This always limits their applications in practice, since the resources of WSNs are quite limited especially in extreme environment. On the other hand, almost all the existing approaches estimate the position and times of the source node at the same time. However, to the best of the authors' knowledge, there are few papers that estimate the unknowns alternately by considering the fact that the original problem is nonlinear only with respect to source position, but it is linear with respect to the clock parameters. This partly motivate us for this paper.

To take full advantage of the natural characteristic of the joint localization and synchronization problem mentioned above, a novel bi-iterative algorithm is proposed in this work. In our bi-iterative algorithm, the location and timings of the source node are computed alternately by decomposing the original problem into two closely related sub-problems respect to the source node position and clock parameters, respectively, that can reduce the computational complexity. The main three contributions of this paper are summarized as follows:

(1) We develop an efficient bi-iterative algorithm to solve the joint localization and synchronization problem from a new point of view that unlike the existing algorithms.
(2) We theoretically analyze the convergence behavior of the proposed method.
(3) Based upon the first-order perturbation analysis, we demonstrate that the proposed algorithm can approximately reach the Cramer–Rao Lower Bound (CRLB) under the mild noise condition.

The rest of this paper is arranged as follows. In Section 2, we first describe the system model. Section 3 establishes the ML estimator. The proposed bi-iterative algorithm is developed in Section 4. Section 5 provides some simulation results to illustrate the effectiveness of our algorithm. Finally, Section 6 concludes this whole paper.

Notation: Throughout this paper, the following notations are used for notational convenience. The special matrices $\mathbf{1}_{M\times 1}$ and $\mathbf{0}_{M\times 1}$ stand for the $M\times 1$ vectors of ones and zeros, respectively. $\mathbf{E}_{M\times 1}$ denotes the length-M column vector of alternating -1 and 1. $\mathbf{I}_N$ is the N-dimensional identity matrix. In addition, the operators $\|\bullet\|_2$, $(\bullet)^{\mathrm{T}}$, $(\bullet)^{-1}$, $E[\bullet]$, $\otimes$ and $\odot$ represent the 2-norm of a vector, the transpose operator, the inverse of a square matrix, the expectation operator, the Kronecker product and the entry-wise product of two matrices, respectively. Moreover, $diag(\bullet)$ is used to denote a diagonal matrix.

2. Localization scenario and problem formulation

In an asynchronous system, assume that the local times of the sensor nodes are different and deviate from the global time, and follow affine model [23]. Then we have

$$t_l = \omega_l t_g + \theta_l, \tag{1}$$

where t_l is the local time of a sensor node, t_g represents the global time; ω_l and θ_l are, respectively, the clock skew and clock offset of the sensor node. Note that the clock skew and offset are different from node to node.

We consider a two-dimensional system model as shown in [23,29]. In the system, assume that there are one unknown target sensor node and N ($N\geq 3$) known anchors which are not lying on a straight line. The i^{th} anchor is located at $\mathbf{s}_i = [x_i, y_i]^{\mathrm{T}}$, $i = 1, 2, \dots, N$, and its clock skew and clock offset are, respectively, denoted by ω_i and θ_i. Let $\mathbf{x} = [x, y]^{\mathrm{T}}$, and ω_x, θ_x be the unknown coordinates and clock parameters of the source node, respectively. In order to determine the unknowns of the source node, two-way message exchange mechanism is employed in the system as shown in Fig. 1. Assume there are M rounds of message exchanges between the source node and the ith anchor. During the mth round ($m = 1, 2, \dots, M$), the source node first transmits a signal at time $T_{i,\,m}$, and the signal is received by the anchor i at time $R_{i,\,m}$. Then a replied massage is sent back from ith anchor at time $\bar{T}_{i,m}$, finally captured by the source node at $\bar{R}_{i,m}$. Note that these time-stamps are measured with respect to the local clock of the corresponding node. It is assumed that during the M rounds of message exchanges, the clock parameters and position of the source node do not be changed (this assumption is reasonable in practice because the duration of the M rounds message passing is very short).