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A nonlinear smoother for target tracking in asynchronous wireless sensor networks

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ABSTRACT

Generally, multiple sensors are deployed to track a target synchronously in wireless sensor networks. However, asynchronous measurements exist intrinsically in multi-rate multi-sensor systems. Asynchronous measurements may also emerge in acoustic sensor networks, owing to the low propagation speed of acoustic signals. In order to handle the target tracking problem with asynchronous measurements, a nonlinear smoothing algorithm based on the fixed-point smoother and the square-root cubature Kalman filter is derived and applied in asynchronous wireless sensor networks for the first time. The estimation precision of the states increases along with the smoothing process, and a sensor can always obtain the optimal estimate of a state before its own next measurement by using the proposed algorithm. The numerical simulations demonstrate that, thanks to the smoothing effect of the fixed-point smoother, the proposed algorithm can obtain not only the remarkable position estimation results of the target, but also even better velocity estimation results. In addition, the proposed algorithm can obtain much more states' estimates than benchmark synchronous target-tracking algorithms, under the same condition of measurement count and communication cost.

1. Introduction

In literatures, various algorithms have been proposed for target tracking in wireless sensor networks (WSNs), and synchronous measurement systems are employed by most of these algorithms [1,2]. Generally, multiple sensors are deployed to track a target synchronously in WSNs. Kalman filters (KF) [3], Particle filters (PF) [4], and their variants [5,6] are used to estimate the states recursively. All the filtering processes can be considered as a Bayesian inference process which can be divided into two steps: the prediction step and the update step [7]. In the prediction step, the to-be-estimated states are predicted based on the current posterior estimates. In the update step, the predicted states are updated with the measurements obtained by the sensors. Under the full consideration of the temporal continuity of the movement trajectory of the target, the synchronous measurements may contribute less to target tracking than to one-shot target localization. In particular, the prior predictions of the to-be-estimated states may have higher precision when the measurement period is shorter, and then the synchronous measurements will contribute less to the posterior estimates based on the precise prior predictions, and vice versa. However, a shorter measurement period will result in more measurements, which lead to more energy consumption.

In addition, synchronous measurements cannot always be obtained all the time. Due to the low propagation speed of acoustic signals [8], the Inter-Sensor Interference (ISI) problem appears with the active sensors in the non-collaborative target tracking system [9]. The sensors have to perform measurements asynchronously in order to avoid the ISI problem. Taking into consideration of the limited propagation speed of acoustic signals, it cannot even be certain that all the sensors can receive the same signal from the target simultaneously in a collaborative target tracking system with acoustic sensors. In other words, the non-ignorable time of flight (TOF) of acoustic signals will lead to a result that the signals simultaneously received by sensors may be emitted from the target at different time. Thus, the strategy that tries to ensure the precision of the estimates by deploying sufficient sensors to track the target synchronously may lose its effectiveness in practice.

Owing to the aforementioned factors, asynchronous wireless sensor networks emerge [10], where sensors perform measure-

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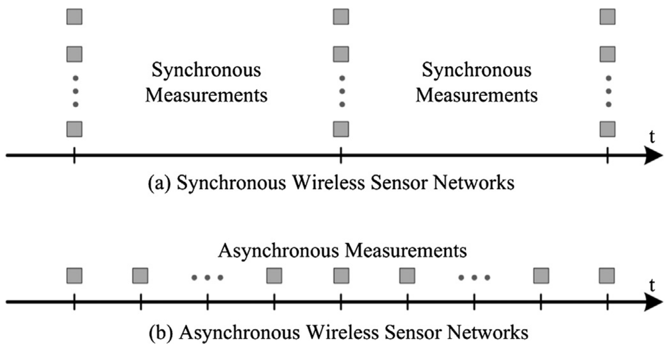

Fig. 1. Synchronous wireless sensor networks vs. asynchronous wireless sensor networks, under the condition of the same measurement count during the same time interval.

ments asynchronously. Under the condition of the same measurement count during the same time interval, asynchronous WSNs have shorter measurement intervals between two sequential and asynchronous measurements than synchronous WSNs, and much more states are measured during the same time interval in asynchronous WSNs, as shown in Fig. 1. Various algorithms have been proposed for target tracking in asynchronous WSNs. Several information fusion algorithms for asynchronous multi-rate multi-sensor systems were proposed in [11–14], and these algorithms could be generally divided into two steps: a) each sensor estimated the states with its own measurements independently, b) the estimated states by each sensor were fused using covariance-intersection methods. Thus, these algorithms could work well in the scenario where each sensor could estimate the states alone, but they may lose their advantages for target tracking in range-only or bearing-only asynchronous WSNs. The asynchronous Particle filters proposed in [15,16] were applicable in range-only asynchronous WSNs. These two algorithms estimated the to-be-estimated states with the most recently received intermediate measurements and the corresponding intermediate states' predicted estimates. Multiple asynchronous measurements were combined to estimate a to-be-estimated state. However, the previous measurements were more suitable to predict than to update the current to-be-estimated state. Therefore, these two algorithms could only achieve much the same or slightly worse tracking performances, compared with benchmark synchronous target-tracking algorithms.

Under the condition of the same measurement count during the same time interval, larger numbers of states of the target are measured by the sensors in asynchronous WSNs, as shown in Fig. 1(b). Thus, if the continuity property of the target's movement trajectory was in full use, the states corresponding to the sequential and asynchronous measurements could be estimated, and the continuity property among the estimated states could be utilized to improve their own estimation precision further. In this paper, a nonlinear smoothing algorithm based on the fixed-point smoother [17] and the square-root cubature Kalman filter [18] is derived and applied in range-only asynchronous WSNs for the first time. The fixed-point smoother has not been widely used in the signal processing field because of the real-time requirement. But, a sensor can always obtain the most precise estimate of a state before its own next measurement by using the proposed algorithm. In addition, thanks to the temporal smoothing effect of the fixed-point smoother, the proposed algorithm can obtain not only the remarkable position estimation results of the target, but also even better velocity estimation results.

The remainder of the paper is organized as follows. Section 2 formulates the target tracking problem in asynchronous wireless sensor networks. Based on the fixed-point smoother and the square-root cubature Kalman filter, a nonlinear smoothing algorithm is derived in Section 3. Numerical simulations and analysis are presented in Section 4. Lastly, Section 5 gives conclusions.

2. Problem formulation

This study is aimed at proposing an algorithm for target tracking in range-only or bearing-only asynchronous WSNs. As shown in Fig. 1(b), the sequential and asynchronous measurements are corresponding to different instants' states. Let n denote the index of a measurement along the discrete time axis in Fig. 1(b), and let τ_n denote the measurement time instant of the n-th measurement. It is assumed that the measurement time instant τ_n has been adjusted so that the measurement $\mathbf{z}_n$ can be considered as the exact measurement of the state $\mathbf{x}_n$. For simplicity of description and analysis, sensors are assumed to perform measurements asynchronously and periodically. Thus, the index of the measurements of all the involved sensors during the k-th measurement period can be described as $\{kN_s + j | j = 1, 2, \ldots, N_s\}$, where k is the index of the measurement period, and N_s denotes the count of the involved sensors which are being deployed to track the target. Moreover, the index of all the measurements associated with sensor j can be described as $\{kN_s + j | k = 1, 2, \ldots,\}$. Meanwhile, in order to distinguish the synchronous measurements from the asynchronous measurements, as shown in Fig. 1, let τ_k denote the measurement time of the k-th synchronous measuring, let $\mathbf{x}_k$ denote the state at time instant τ_k, and let $\mathbf{z}_k$ denote the synchronous measurements of the state $\mathbf{x}_k$. The synchronous measurement systems will be employed in the simulations for comparison, to demonstrate the advantages of the proposed algorithm.

A two-dimensional wireless sensor network is utilized in this paper to exhibit the target tracking process. The discrete-time dynamics of the target can be described as

$$\mathbf{x}_{n+1} = \mathbf{F}_n \mathbf{x}_n + \mathbf{u}_n \tag{1}$$

where the state $\mathbf{x}_n = [x_{1,n}, \dot{x}_{1,n}, x_{2,n}, \dot{x}_{2,n}]^{\mathrm{T}}$ consists of the position component $[x_{1,n}, x_{2,n}]^{\mathrm{T}}$ and the velocity component $[\dot{x}_{1,n}, \dot{x}_{2,n}]^{\mathrm{T}}$ of the target at the time instant τ_n, the process noise $\mathbf{u}_n \backsim \mathcal{N}(\mathbf{0}, \mathbf{Q}_n)$ has a non-singular covariance and is related to the time interval $(\tau_{n+1} - \tau_n)$, and $\mathbf{F}_n$ is the state transition matrix related to the time interval $(\tau_{n+1} - \tau_n)$.

A time of flight (TOF) measurement model is utilized by each sensor,

$$\mathbf{z}_n = h(\mathbf{x}_n) + \mathbf{v}_n = \frac{\|\boldsymbol{r}_n - \boldsymbol{l}_j\|}{\rho} + \mathbf{v}_n \tag{2}$$

where $\boldsymbol{r}_n = [x_{1,n}, x_{2,n}]^{\mathrm{T}}$ is the estimated location of the target, $\boldsymbol{l}_j$ is the location of sensor j, ρ, is the propagation speed of the signal, $\mathbf{v}_n \backsim \mathcal{N}(0, R_n)$ with $R_n = \sigma_n^2$ is the measurement noise, and $\|\cdot\|$ is the Euclidean distance. The location $\boldsymbol{l}_j$, $j \in (1, \ldots, N_s)$, the covariance R_n, and the propagation speed ρ are all assumed to be constant and known. A single such measurement cannot be used to estimate its corresponding state completely, because it has lower dimensionality than the state.

3. Square-root fixed-point cubature Kalman smoother

A nonlinear smoothing algorithm based on the fixed-point smoother and the square-root cubature Kalman filter is derived in this section for the first time. The temporal smoothing effect of the fixed-point smoother is utilized in this study to improve the estimates of the states in asynchronous WSNs.

The fixed-point smoother (FPS) refers to a methodology that can be used to efficiently compute the optimal estimate (i.e., $p(\mathbf{x}_n|\mathbf{z}_{1:n+N})$) of a fixed-time state of a state space model, given