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# Event-triggered cooperative target tracking in wireless sensor networks

Lu Kelin [a], Zhou Rui [a,*], Li Hao [b]

[a] School of Automation Science and Electrical Engineering, Beihang University, Beijing 100083, China
[b] AVIC Chengdu Aircraft Design & Research Institute, Chengdu 610091, China

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**Abstract** Since the issues of low communication bandwidth supply and limited battery capacity are very crucial for wireless sensor networks, this paper focuses on the problem of event-triggered cooperative target tracking based on set-membership information filtering. We study some fundamental properties of the set-membership information filter with multiple sensor measurements. First, a sufficient condition is derived for the set-membership information filter, under which the boundedness of the outer ellipsoidal approximation set of the estimation means is guaranteed. Second, the equivalence property between the parallel and sequential versions of the set-membership information filter is presented. Finally, the results are applied to a 1D event-triggered target tracking scenario in which the negative information is exploited in the sense that the measurements that do not satisfy the triggering conditions are modelled as set-membership measurements. The tracking performance of the proposed method is validated with extensive Monte Carlo simulations.



## 1. Introduction

In recent years, cooperative target tracking in wireless sensor networks (WSNs) has a wide range of applications in the field of intelligence, surveillance and reconnaissance (ISR).[1–3] The application of distributed WSNs provides a competent method for battlefield information collection and a robust scheme for moving target tracking[4,5] in a complex and interference-rich environment. However, the limited network resources in terms of energy and communication bandwidth set a constraint on the ability of WSNs.[6–8] Since the sensors are dispersed via airdrop or cannon fire in a lot of practical scenarios,[9] their batteries are difficult to be recharged or replaced. Thus, an energy-saving tracking strategy is demanded to conserve network energy and extend network life.

For wireless ad hoc networks, the energy consumption depends heavily on the wireless communication.[10] Since WSNs face stringent energy limits, forcing all sensors to communicate with the fusion center (FC) at full rate is apparently not

* Corresponding author. Tel.: +86 10 82339232.
E-mail addresses: klu@buaa.edu.cn (K. Lu), zhr@buaa.edu.cn (R. Zhou), lynn.lihao@163.com (H. Li).

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affordable. Therefore, an energy-saving strategy in our tracking architecture is to reduce the communication frequency while guarantee an acceptable tracking accuracy.[11,12] Event-triggered estimation is a promising alternative to fulfill such imperative requirement.[13] In contrast to sending the measurements periodically, the local sensors employ various event sampling strategies to determine whether to send up-to-date measurements to the remote FC, such as Matched Sampling,[14] Integral Sampling,[15] Send-on-Delta (SOD)[16] and Variance-based Triggering.[17] As a result, the event-triggered strategy is to estimate the state based on the intermittent observations[18] that satisfy the triggering conditions, but this cannot be applied straightforwardly in target tracking applications because the improper design of triggering thresholds might result in the loss of track[19,20] as the FC receives no observation at a number of consecutive time steps.

In cases that the sensors determine not to send their current measurements, some "negative information"[21] is implicitly available to the remote FC without additional communication. For example, when the SOD method is employed, no measurement transmission from one specific sensor implies that the value of the current measurement does not deviate too much from the value of the last transmitted measurement,[22] which suggests that although the exact value of the current measurement is unknown to the FC, it lies in a set formulated by the SOD triggering condition. In order to better exploit this "negative information", as well as to integrate it into the Bayesian state estimation framework, several set-membership state estimators[23–25] have been proposed, where the uncertainty of the negative information is modelled as a set of Gaussian densities. In Ref.[26], a generalization of the standard Kalman filter is developed to solve the problem of set-membership measurement for the single sensor. The work in Ref.[27] reveals that the information form of set-membership filtering consists of advantageous properties especially when multiple set-membership measurements are received. Despite the great deal of effort that has been dedicated to it, several problems remain open, which are of significant importance in studying the set-membership filter and its application to the problem of event-triggered cooperative target tracking in WSNs. The first issue is that the boundedness of the set of the estimation means has not been investigated systematically when the set-membership measurement is considered.[27,28] Another issue is to explore the equivalence between the parallel and recursive implementations of the set-membership information filter, and particularly since the Minkowski sum of ellipsoids[29] might not be an ellipsoid, some approximation of the exact estimation result is inevitable.

In this paper, we study the boundedness of the set of the estimation means with the information form, where a sufficient condition is proved, under which the outer ellipsoidal approximation set is asymptotically bounded. We also present the equivalence between the parallel and sequential set-membership information filters. Finally, the set-membership information filter is applied to the problem of event-triggered cooperative target tracking, and the performance of the proposed tracking strategy is further validated with extensive Monte Carlo simulations.

## 2. Problem formulation

For a random vector $\boldsymbol{x} \in \mathbf{R}^n$, we use $E(\boldsymbol{x})$ and $\mathrm{Cov}(\boldsymbol{x})$ to denote its mean and covariance respectively. For a matrix $\boldsymbol{A} \in \mathbf{R}^{n\times n}$, we define $\mathrm{tr}(\boldsymbol{A})$ as its trace. Given $\boldsymbol{S} \in \mathbf{R}^{n\times n} > \mathbf{0}$, i.e., $\boldsymbol{S}$ is positive definite, an ellipsoidal set $\mathcal{X} = \varepsilon(\boldsymbol{c}, \boldsymbol{S})$ is represented as

$$\mathcal{X} \triangleq \varepsilon(\boldsymbol{c}, \boldsymbol{S}) = \left\{ \boldsymbol{x} \in \mathbf{R}^n | (\boldsymbol{x}-\boldsymbol{c})^{\mathrm{T}} \boldsymbol{S}^{-1} (\boldsymbol{x}-\boldsymbol{c}) \leqslant 1 \right\} \tag{1}$$

For two ellipsoidal sets $\mathcal{X}$ and $\mathcal{Y}$, let $\mathcal{X} \oplus \mathcal{Y}$ denotes their Minkowski sum, namely $\mathcal{X} \oplus \mathcal{Y} \triangleq \{\boldsymbol{x}+\boldsymbol{y} | \boldsymbol{x} \in \mathcal{X}, \boldsymbol{y} \in \mathcal{Y}\}$, and we have $\sum_{i=1}^{N} \mathcal{X}_i \triangleq \mathcal{X}_1 \oplus \mathcal{X}_2 \oplus \cdots \oplus \mathcal{X}_N$.

We consider a linear time-invariant dynamic system that evolves in discrete time and is perturbed by Gaussian white noise as follows:

$$\boldsymbol{x}(k) = \boldsymbol{F}\boldsymbol{x}(k-1) + \boldsymbol{w}(k) \tag{2}$$

where $\boldsymbol{x} \in \mathbf{R}^n$; $\boldsymbol{w} \sim N(\mathbf{0}, \boldsymbol{Q})$; $\boldsymbol{F}$ is the transition matrix of the dynamic model; and $\boldsymbol{Q}$ is the covariance of the process noise. We assume that $(\boldsymbol{F}, \boldsymbol{Q})$ is stabilizable.[30] The state $\boldsymbol{x}$ is measured with $N$ sensors as

$$\boldsymbol{z}_i(k) = \boldsymbol{H}_i \boldsymbol{x}(k) + \boldsymbol{v}_i(k) \quad \text{for} \quad i = 1, 2, \ldots, N \tag{3}$$

where $\boldsymbol{v}_i \sim N(\mathbf{0}, \boldsymbol{R}_i)$ denotes the measurement noise, $\boldsymbol{R}_i$ the covariance of the measurement noise for the $i$th sensor; $N$ is the number of the sensors; $\boldsymbol{H}_i$ is the measurement model matrix. We also assume that $(\boldsymbol{F}, \boldsymbol{H})$ is detectable,[30] where $\boldsymbol{H} = [\boldsymbol{H}_1, \boldsymbol{H}_2, \ldots, \boldsymbol{H}_N]^{\mathrm{T}}$ and $\boldsymbol{R} = \mathrm{diag}(\boldsymbol{R}_1, \boldsymbol{R}_2, \ldots, \boldsymbol{R}_N)$. In addition to the stochastic measurement noise $\boldsymbol{v}_i$, we further consider that the obtained measurement consists of an unknown but bounded error $\boldsymbol{e}_i(k)$, namely

$$\hat{\boldsymbol{z}}_i(k) = \boldsymbol{H}_i \boldsymbol{x}(k) + \boldsymbol{v}_i(k) + \boldsymbol{e}_i(k) = \boldsymbol{z}_i(k) + \boldsymbol{e}_i(k) \tag{4}$$

where the uncertainty of $\boldsymbol{e}_i(k)$ is confined to an ellipsoidal set as

$$\boldsymbol{e}_i(k) \in \varepsilon(\mathbf{0}, \boldsymbol{S}_{\boldsymbol{e}_i(k)}) \tag{5}$$

With respect to the fact that the uniqueness of the measurement $\hat{\boldsymbol{z}}_i$ cannot be maintained due to the uncertainty of $\boldsymbol{e}_i(k)$, the set-membership[31] measurement $\mathcal{Z}_i$ will be used as a replacement:

$$\mathcal{Z}_i(k) = \{\hat{\boldsymbol{z}}_i(k) - \boldsymbol{e}_i(k) | \boldsymbol{e}_i(k) \in \varepsilon(\mathbf{0}, \boldsymbol{S}_{\boldsymbol{e}_i(k)})\} = \varepsilon(\hat{\boldsymbol{z}}_i(k), \boldsymbol{S}_{\boldsymbol{e}_i(k)}) \tag{6}$$

To cope with the set-membership uncertainty of $\mathcal{Z}_i$, one feasible manner is to model the uncertainty by a set of Gaussian densities, which gives rise to the set-membership Kalman filter[32] and set-membership information filter.[27] We know that the standard information filter embodies an algebraic reformulation of the Kalman filter, which provides an easier update phase for the distributed estimation architecture by estimating the information about the state rather than the state itself.[33] More exactly, the information state

$$\boldsymbol{y} = \boldsymbol{P}^{-1}\hat{\boldsymbol{x}} \tag{7}$$

where $\boldsymbol{P}$ is estimation covariance matrix and $\hat{\boldsymbol{x}}$ the estimation mean; and the information matrix

$$\boldsymbol{Y} = \boldsymbol{P}^{-1} \tag{8}$$

are the quantities to be calculated at the prediction and update steps. In the presence of additional set-membership uncertainties, an ellipsoidal set $\varepsilon(\hat{\boldsymbol{x}}, \boldsymbol{S}_{\hat{\boldsymbol{x}}})$ of estimation means has to be processed in its information form, which is obtained by an affine transformation[34]:

$$\mathcal{Y} = \boldsymbol{P}^{-1}\varepsilon(\hat{\boldsymbol{x}}, \boldsymbol{S}_{\hat{\boldsymbol{x}}}) = \varepsilon\left(\boldsymbol{P}^{-1}\hat{\boldsymbol{x}}, \boldsymbol{P}^{-1}\boldsymbol{S}_{\hat{\boldsymbol{x}}}(\boldsymbol{P}^{-1})^{\mathrm{T}}\right) = \varepsilon(\boldsymbol{y}, \boldsymbol{S}_{\mathcal{Y}}) \tag{9}$$