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ML estimation of transition probabilities for an unknown maneuvering emitter tracking ☆

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ABSTRACT

We consider the problem of an unknown maneuvering emitter tracking by a wireless sensor network with time difference of arrival (TDOA) and frequency difference of arrival (FDOA) measurements. Interacting multiple models combined with square-root cubature Kalman filter with correlated noises (IMM-SCKF-CN) is proposed to update the parameters in the maneuvering emitter tracking. Essential to this tracking framework is the Markov transition probability matrix (TPM) which governs the jumps between multiple dynamic motion models for the maneuvering target. However, in practice, the TPM is unknown and has to be estimated. In this paper, we consider the maximum likelihood (ML) estimation of the TPM and propose a recursive algorithm based on the *improved weighted* analytical center cutting plane method (ACCPM). Compared with some batch ML methods, the resulting recursive ML estimation method has a much lower per sample complexity. Simulation results show the efficacy of the proposed method with greatly improved tracking performance.

1. Introduction

Hybrid-state systems or jump Markov systems (JMSs) are used in many applications of signal processing, control theory and communications [1]. In maneuvering target tracking, they can be defined as continuous-value as well as discrete-value dynamic systems, whereby multiple models representing the target motion equations switch from one to another according to a Markov chain. Though there are many means of achieving the state estimation of a maneuvering target, a popular approach is to model the system as a JMS with known TPM. However, in practice, the TPM is always unknown and has to be precisely estimated, otherwise, performance of the state estimation will be dramatically degraded [2,3]. Therefore, the accurate estimate of the TPM while allowing the multiple models adaptively in the course of processing measurements is necessary for JMSs. In a wireless sensor network with synchronized sensor nodes, detection, localization, and tracking are always performed by either TDOA or FDOA or both [4,5]. In this paper, we focus on the TPM estimate based on the maximum likelihood criterion using TDOA and FDOA measurements in the JMSs.

Many kinds of tracking filters are used for maneuvering target tracking [6–21]. One commonly used tracking filters are linear tracking filters [6–8] including the standard Kalman filter and lots of improved versions. Although they are powerful tools for state estimation of the linear dynamic system, they are not able to meet the increasing demands

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from applications as more and more complicated nonlinear tracking problems are emerging. Extended Kalman filter (EKF) [9,10] is one commonly used nonlinear tracking filter. Though the performance of the filter is better than what Kalman filter can provide, the application capability of EKF is significantly limited because of its low accuracy, bad stability, slow convergence and high running complexity induced by the computation of the Jacobian matrix. Unscented Kalman filter (UKF) [11–13] is another popular used nonlinear tracking filter. Though there have been many achievements by UKF, it can easily diverge [13,14]. Furthermore, the performance will obviously decrease when the system state dimensionality is relatively high. Recently, particle filter (PF) [15–17] is more and more widely used in various fields. Though the state estimation accuracy is greatly improved compared with EKF and UKF, PF can easily lead to tremendous computational complexity [16], which restricts its application in real-time systems. Square-root cubature Kalman filter (SCKF) is one of the nonlinear filters that can achieve best trade off between accuracy and efficiency [18–20]. It has a good ability to deal with the high dimensional state. Most importantly, it uses the *QR* decomposition to avoid the square-root operation of the prediction covariance matrix and thus ensures the continuity of the filtering process. Furthermore, there exists correlation between process and measurement noise in maneuvering target tracking [21], we use SCKF with correlated noises, SCKF-CN in short, [19] to deal with such a difficult situation.

For maneuvering target tracking, there are usually multiple states to transmit from one to another. Full-hypothesis-tree [1] is the optimal algorithm in the minimum mean square sense to estimate the states. However, this algorithm is infeasible in practice because of its exponentially growing computational time and memory. In order to overcome this shortcoming, many suboptimal merging algorithms with limited complexity are presented. Generalized Pseudo Bayesian of the first order (GPB1) and Generalized Pseudo Bayesian of the second order (GPB2) are the two usually used dynamic multiple models estimators. The most popular used multiple models estimator for switching models is IMM estimator whose computational complexity is the same as that of GPB1 estimator while the performance is almost as well as that of GPB2 estimator. This indicates that the IMM algorithm achieves a good trade off between computational cost and performance, thus often used in the maneuvering target tracking.

There are some publications involving to TPM estimation. In [22], the truncated ML estimator was developed, where the unknown TPM was chosen from a finite candidate set. However, the computational complexity is quite high and the choice of candidate set in some practical applications is difficult. The recursive Kullback–Leibler (KL) was developed in [23], where the KL divergence between the likelihood of the observations given by the TPM and the true likelihood was approximately minimized. An expectation–maximization-type approximation to the original ML problem in JMLs was derived from [24]. However, this method is very computationally expensive. Online recursive TPM estimation using the MMSE criterion was presented in [2], but the estimation accuracy and computational time are not satisfied. In [25], a convex formulation for ML estimation of TPM was established. Though the estimation performance of the TPM is improved compared with [2], the computation complexity is too high due to employing PF as model matching filter. An improved design method based on convex optimization was considered in [26]. However, the design only considered the linear system model and only used the linear Kalman filter as mode matching filter. In [27], analytical center cutting plane method [30], together with IMM-EKF, was used to track an unknown maneuvering emitter. Though the complexity has been greatly reduced compared with the best method numerical integral (NI) in [2], the performance of tracking is still not satisfying.

In this paper, we consider the problem of maximum likelihood estimation of the TPM. The main contributions of this paper lie in the following aspects. First, since the ML estimate of the TPM corresponds to the analytic center of a polytope defined by the measurements, we present the *improved weighted* ACCPM, which is the extension of the algorithm in [27], to recursively update the ML TPM estimate. In this way, the ML TPM estimation can be performed with much higher accuracy and substantially lower complexity per sample than some batch methods, which is very important in practice. Second, SCKF has many outstanding properties which make it very suitable for maneuvering target tracking. Further, by considering measurement noise cross-correlated process noise one time step apart [18,19,21, *references therein*], we present IMM-SCKF-CN to update the parameters in the optimization problem for the TPM estimate. Third, we provide extensive numerical examples. Simulation results show that, in the JMSs with joint TDOA and FDOA measurements, the *improved weighted* ACCPM is an efficient recursive TPM estimation method, which, together with IMM-SCKF-CN, can yield a promising tracking performance.

2. System model

Consider the discrete JMS [28] with TDOA and FDOA measurements:

$$\mathbf{x}(k) = \mathbf{F}(k-1, m(k))\mathbf{x}(k-1) + \mathbf{C}_r\mathbf{c}(m(k)) + \mathbf{v}(k-1, m(k)), \quad (1)$$

$$\mathbf{z}(k) = \begin{bmatrix} \mathbf{z}^t(k) \\ \mathbf{z}^f(k) \end{bmatrix} = \begin{bmatrix} \mathbf{h}^t\left[\mathbf{x}(k), \{\mathbf{s}^{(i)}(k)\}\right] + \boldsymbol{\omega}^t(k) \\ \mathbf{h}^f\left[\mathbf{e}(k), \{\mathbf{s}^{(i)}(k)\}\right] + \boldsymbol{\omega}^f(k) \end{bmatrix}, \quad i = 1, 2, \ldots, M, \quad (2)$$

where k denotes time, $\mathbf{x}(k) = [x(k), y(k), z(k), \dot{x}(k), \dot{y}(k), \dot{z}(k)]'$ denotes the base state vector corresponding to the location and velocity of the moving emitter, $\mathbf{s}^{(i)}(k)$ denotes the location of the i-th sensor, $\mathbf{C}_r$ denotes the constant control matrix, $\mathbf{c}(m(k))$ denotes the control vector, $\mathbf{v}(k)$, $\boldsymbol{\omega}^t(k)$ and $\boldsymbol{\omega}^f(k)$ are assumed to be Gaussian distributed, and $\mathbf{h}^t(k)$ and $\mathbf{h}^f(k)$ respectively denote the noise-free TDOA and FDOA measurement vector. $m(k)$ is the modal state with $m(k) \in \mathbb{M} \triangleq \{1, 2, \ldots, r\}$. Here, we denote $m(k)$ as a Markov chain with initial and transition probability respectively denoted by

$$\mu_j(0) = P(m_j(0)), \quad (3)$$