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Multi-target FIR tracking algorithm for Markov jump linear systems based on true-target decision-making

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ABSTRACT

Most existing multi-target tracking (MTT) algorithms are based on Kalman filters (KFs). However, KFs exhibit poor estimation performance or even diverge when system models have parameter uncertainties. To overcome this drawback, finite impulse response (FIR) filters have been studied; these are more robust against model uncertainty than KFs. In this paper, we propose a novel MTT algorithm based on FIR filtering for Markov jump linear systems (MJLSs). The proposed algorithm is called the multi-target FIR tracking algorithm (MTFTA). The MTFTA is based on the decision-making process to identify the true-target's state among candidate states. The true-target decision-making process utilizes the likelihood function and the Mahalanobis distance. We show that the proposed MTFTA exhibits better robustness against model parameter uncertainties than the conventional KF-based algorithm.

1. Introduction

Multi-target tracking (MTT) estimates the number and states of targets from noisy measurements. MTT algorithms have been used in many engineering applications, including radar systems, video surveillance, and intelligent transportation systems [1–5]. There are various kinds of MTT algorithms, but they can be categorized into two groups. One is MTT algorithms based on data association (DA) techniques. The global nearest neighbor (GNN) [6], joint probabilistic data association (JPDA) [7], and multiple hypothesis tracking (MHT) [8] belong to this group. The other group is based on the random finite set (RFS) approach proposed by Mahler [9] for overcoming the high computational burden of DA techniques. The probability hypothesis density (PHD) filter [9] is a representative MTT algorithm based on the RFS. However, the PHD filter requires multiple dimensional integrals in the propagation of Bayes recursion and has no closed-form solutions. To obtain a closed-form solution of the PHD filter, the Gaussian mixture PHD (GM-PHD) filter was proposed by Vo [10].

Recently, Markov jump systems (MJSs) have attracted significant attention in various fields due to their modeling capability of practical systems, such as aircraft, power, and communication systems [11–18]. In the MTT problem, the Markov jump linear system (MJLS) [19–21] has been widely used to describe the changeable motion of maneuvering targets [22]. DA techniques are combined with the interactive multi-model (IMM) algorithm to solve MTT problems for MJLS [23,24]. In the framework of the PHD filter, GM-PHD filters for MJLS have been proposed [25–27].

Most existing MTT algorithms for MJLS are based on Kalman filters (KFs). However, it is known that KFs exhibit poor estimation performance or even diverge when system models have parameter uncertainties [28–30]. This is because KFs have an infinite impulse response (IIR) structure. State estimators with an IIR structure [30,31] use all past input/output information to produce state estimates; thus, the errors caused by differences between the true information and the given information of system models accumulate over time. To overcome this drawback of KFs with an IIR structure, state estimators with a finite impulse response (FIR) structure, referred to as FIR filters [32–42], were developed. The FIR filters use the recent finite input/output information of the system to produce state estimates. Thus, FIR filters can prevent error accumulation and have bounded-input, bounded-output (BIBO) stability. A state estimator with a FIR structure was originally developed by Jazwinski [32]. Kwon developed the optimal FIR filter with batch form [33] and the receding horizon Kalman FIR (RHKF) filter with recursive form [34]. Ahn developed several robust FIR filters [35–39], such as the H_∞ FIR filter [35,36] and the l_∞ FIR filter [38], for deterministic systems. Pak [41] developed FIR filters using variable horizon size and used them in tracking applications. The FIR filters mentioned above have shown their superior robustness against modeling errors and incorrect noise information compared with the KFs.

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The information on a target's motion and noise statistics is usually uncertain in MTT problems. The MTT algorithms based on KFs may exhibit poor tracking performance with incorrect model information. Therefore, in this paper, we propose a novel FIR filter-based MTT algorithm for MJLS. The proposed algorithm is called the multi-target FIR tracking algorithm (MTFTA). The MTFTA follows the RFS approach to avoid the high computational burden of DA techniques. The RFS approach generates many candidates of the target's state, called the hypotheses, which are obtained through state estimation using noisy measurements. Among the hypotheses, the MTFTA selects the reliable ones. Next, the MTFTA decides which is the true-target's state among the reliable hypotheses. This decision-making process is based on the likelihood function and the Mahalanobis distance. Through this two-step decision-making process, the estimated states of the true targets are obtained. Under the conditions of the uncertain model parameters and the incorrect noise information, the MTFTA is compared to the conventional KF-based MTT algorithm, the GM-PHD filter. We show that the MTFTA has superior robustness against model parameter uncertainty and incorrect noise information compared to the GM-PHD filter.

This paper is organized as follows. In Section 2, we propose the MTFTA for MJLS. In Section 3, extensive simulation results are presented to demonstrate the performance of the MTFTA. Finally, conclusions are presented in Section 4.

2. MTFTA for MJLSs based on true-target decision-making

2.1. FIR filter for MJLSs

In this subsection, we introduce the FIR filter for MJLS [42]. This will be used for the MTFTA in the next section. Consider the following MJLS model [42,43]:

$$x_{k+1} = A(r(k))x_k + Gw_k, \quad w_k \sim (0, Q), \tag{1}$$

$$y_k = C(r(k))x_k + v_k, \quad v_k \sim (0, R), \tag{2}$$

where $x_k \in \Re^n$ and $y_k \in \Re^p$ are the state and measurement vectors at time k, respectively; the process and measurement noises, w_k and v_k, are zero-mean white Gaussian and mutually uncorrelated; $A(r(k))$, $C(r(k))$, and G are constant matrices with appropriate dimensions (in particular, the matrix $A(r(k))$ is assumed to be nonsingular). Here, $r(k)$ is the regime (model) variable in effect during the sampling period $(k, k+1]$, which is used for the model transition. In the MJLS, the model transition is determined by the transitional probability, π_{ij}, defined by

$$\pi_{ij} = P(r(k) = j \mid r(k-1) = i), \quad (i, j \in S), \tag{3}$$

$$S = \{1, 2, \ldots, s\}, \tag{4}$$

where $P(r(k) = j \mid r(k-1) = i)$ is the probability of model transition from the ith model to the jth model, S is the set of regime variables, and s is the number of models.

The FIR filter for MJLS models (1) and (2) is represented as follows [42]:

$$\hat{x}_{k|k-1} \triangleq \sum_{i=1}^{N} H_{i,\mathbf{r}(k)} y_{k-i} \tag{5}$$

$$= \tilde{H}_{\mathbf{r}(k)} Y_{k-1}, \tag{6}$$

where $\tilde{H}_{\mathbf{r}(k)}$ is the FIR filter gain, Y_{k-1} is the augmented measurement vector, and $\mathbf{r}(k)$ is the set of switching information on the horizon $[k-N, k-1]$ defined by, respectively,

$$\tilde{H}_{\mathbf{r}(k)} \triangleq \left[H_{N,\mathbf{r}(k)} \; H_{N-1,\mathbf{r}(k)} \; \cdots \; H_{1,\mathbf{r}(k)} \right], \tag{7}$$

$$Y_{k-1} \triangleq \left[y_{k-N}^T \; y_{k-N+1}^T \; \cdots \; y_{k-1}^T \right]^T, \tag{8}$$

$$\mathbf{r}(k) \triangleq \{r(k-N), r(k-N+1), \cdots, r(k-1)\}. \tag{9}$$

The FIR filter gain $\tilde{H}_{\mathbf{r}(k)}$ is represented as follows:

$$\tilde{H}_{\mathbf{r}(k)} = (\tilde{C}_{N,\mathbf{r}(k)}^T \tilde{\Xi}_{N,\mathbf{r}(k)}^{-1} \tilde{C}_{N,\mathbf{r}(k)})^{-1} \tilde{C}_{N,\mathbf{r}(k)}^T \tilde{\Xi}_{N,\mathbf{r}(k)}^{-1}, \tag{10}$$

where

$$\tilde{C}_{N,\mathbf{r}(k)} \triangleq \begin{bmatrix} C(r(k-N))A^{-1}(r(k-N)) \cdots A^{-1}(r(k-1)) \\ C(r(k-N+1))A^{-1}(r(k-N+1)) \cdots A^{-1}(r(k-1)) \\ \vdots \\ C(r(k-2))A^{-1}(r(k-2))A^{-1}(r(k-1)) \\ C(r(k-1))A^{-1}(r(k-1)) \end{bmatrix}, \tag{11}$$

$$\tilde{\Xi}_{N,\mathbf{r}(k)} \triangleq \tilde{G}_{N,\mathbf{r}(k)} Q_N \tilde{G}_{N,\mathbf{r}(k)}^T + R_N, \tag{12}$$

$$Q_N \triangleq [diag(\overbrace{Q \; Q \; \cdots \; Q}^{N})], \tag{13}$$

$$R_N \triangleq [diag(\overbrace{R \; R \; \cdots \; R}^{N})], \tag{14}$$

$$\tilde{G}_{N,\mathbf{r}(k)} \triangleq -\begin{bmatrix} \Lambda_{11} & \Lambda_{12} & \cdots & \Lambda_{14} & \Lambda_{15} \\ 0 & \Lambda_{22} & \cdots & \Lambda_{24} & \Lambda_{25} \\ 0 & 0 & \cdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \Lambda_{44} & \Lambda_{45} \\ 0 & 0 & \cdots & \cdots & \Lambda_{55} \end{bmatrix}, \tag{15}$$

$$\Lambda_{11} \triangleq C(r(k-N))A^{-1}(r(k-N))G,$$
$$\Lambda_{12} \triangleq C(r(k-N))A^{-1}(r(k-N))A^{-1}(r(k-N+1))G,$$
$$\Lambda_{14} \triangleq C(r(k-N))A^{-1}(r(k-N)) \cdots A^{-1}(r(k-2))G,$$
$$\Lambda_{15} \triangleq C(r(k-N))A^{-1}(r(k-N)) \cdots A^{-1}(r(k-1))G,$$
$$\Lambda_{22} \triangleq C(r(k-N+1))A^{-1}(r(k-N+1))G,$$
$$\Lambda_{24} \triangleq C(r(k-N+1))A^{-1}(r(k-N+1)) \cdots A^{-1}(r(k-2))G,$$
$$\Lambda_{25} \triangleq C(r(k-N+1))A^{-1}(r(k-N+1)) \cdots A^{-1}(r(k-1))G,$$
$$\Lambda_{44} \triangleq C(r(k-2))A^{-1}(r(k-2))G,$$
$$\Lambda_{45} \triangleq C(r(k-2))A^{-1}(r(k-2))A^{-1}(r(k-1))G,$$
$$\Lambda_{55} \triangleq C(r(k-1))A^{-1}(r(k-1))G.$$

2.2. MTFTA for MJLSs

As explained in the previous section, the FIR filtering requires the measurement trajectory for the time interval $[k-N, k-1]$, which was represented in an augmented measurement vector form in (8). In the MTT problem, simultaneous multiple measurements exist; thus, the measurement trajectory becomes complicated. At time $k-N$, we assume that multiple measurements exist from $y_{k-N,1}$ to $y_{k-N,m(k-N)}$, where $m(k-N)$ is the number of measurements at time $k-N$. Since the number of measurements is unpredictable (i.e., random), the set of measurements $\mathbf{Y}_{k-N} = \{y_{k-N,1}, y_{k-N,2}, \ldots, y_{k-N,m(k-N)}\}$ can be considered as a RFS. We then define the set of $\mathbf{Y}_i$ for $i = k-N, k-N+1, \ldots, k-1$ as follows:

$$S_{y,k} = \{\mathbf{Y}_{k-N}, \mathbf{Y}_{k-N+1}, \ldots, \mathbf{Y}_{k-1}\}, \tag{16}$$

To perform the FIR filtering, it is necessary to establish the measurement trajectory by combining N measurements. The measure trajectory is called a path and is given by

$$Path_k^j = \{y_i^j \mid y_i^j \text{ is on } j\text{th path}, \; y_i^j \in \mathbf{Y}_i, \text{ for } i = [k-N, k-1]\}. \tag{17}$$

Fig. 1 represents the paths, which are constructed by combining N measurements on the time interval $[k-N, k-1]$. The maximum