Automatica 47 (2011) 92–98

Contents lists available at ScienceDirect

Automatica

journal homepage: www.elsevier.com/locate/automatica

Brief paper

A switched IMM-Extended Viterbi estimator-based algorithm for maneuvering target tracking☆

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ARTICLE INFO

Article history:
Received 13 December 2008
Received in revised form
9 June 2010
Accepted 14 August 2010
Available online 20 November 2010

Keywords:
State estimation
Target tracking
Markov jump linear systems
Interacting multiple model-extended Viterbi (IMM-EV) estimators
Switched IMM-EV algorithms

ABSTRACT

This paper presents a new algorithm for tracking a maneuvering target modeled as a class of Markov jump linear systems. The proposed algorithm consists of two interacting multiple model-extended Viterbi (IMM-EV) algorithms, coupled with proposed detection schemes for maneuver occurrences and terminations as well as for switching initializations. Combined performance strengths of the two IMM-EV algorithms are utilized via switching from one IMM-EV algorithm to the other. Appropriate design parameter values are derived for the detection schemes of maneuver occurrences and terminations. The results demonstrate that the proposed algorithm can be a viable alternative to several well-known tracking methods.

1. Introduction

Over the past three decades, schemes for state estimation of Markov jump linear systems (MJLS) have been investigated considerably by many researchers (e.g. Blom & Bar-Shalom, 1988; Costa, Fragoso, & Marques, 2005; Tugnait, 1982a,b, and the references therein). In particular, the interacting multiple model (IMM) algorithm of Blom and Bar-Shalom (1988) has been popular for target tracking application (Li & Bar-Shalom, 1993) in which target motions are covered by the dynamics of an MJLS. Recently, several algorithms for possible improvements to the IMM algorithm have been proposed based on a variable structure multiple model design (Li & Zhang, 2000), or the incorporation of an alternating expectation conditional maximization method into the IMM (Johnston & Krishnamurthy, 2001), or the integration of an extended Viterbi algorithm with the IMM (Ho & Chen, 2006).

The objective of this paper is to present a new tracking algorithm that can achieve better performance, making it a viable alternative to the aforementioned methods. The proposed algorithm consists of two interacting multiple model-extended Viterbi (IMM-EV) algorithms of Ho and Chen (2006) in conjunction with proposed maneuver detection and termination schemes. Switches between the two IMM-EV algorithms are utilized for their combined functional strengths. This is motivated by the fact that some IMM-EV algorithms may yield more accurate state estimates efficiently during constant-velocity tracking while other IMM-EV algorithms may perform better during maneuver tracking. Our switching approach conceptually parallels that of the variable-dimension (vd) filter of Bar-Shalom and Birmiwal (1982) which involves switching from a Kalman filter (KF) based on one model to a KF based on the other model. The proposed algorithm can outperform the vd filter substantially.

The proposed algorithm is developed as follows. To handle maneuver detection in a tractable manner, we focus on tracking models without exogenous control inputs. Like the models of Willsky and Jones (1976), the models employed herein can also be used for fault detection. We derive design parameter values for the maneuver detection scheme in which the statistics of innovations may adequately serve as a chi-squared test for the significance of a maneuver. The results can also be applied to the scheme for detecting maneuver termination in which the statistics of acceleration estimates (if acceleration estimates are state components) may appropriately be used as a chi-squared test. We provide initializations of the proposed algorithm for situations where switching from an IMM-EV to the other takes place.

☆ This work was supported in part by National Science Council of Taiwan under contract #NSC 96-2221-E033-044. The material in this paper was partially presented at the IFAC World Congress, July 6–11 2008, Seoul, Korea. This paper was recommended for publication in revised form by Associate Editor Giuseppe De Nicolao under the direction of Editor Ian R. Petersen.

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0005-1098/$ – see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.automatica.2010.10.005

This paper is an extended and improved version of the work of Ho (2008) and is organized as follows: Section 2 describes target models and briefly reviews the IMM-EV algorithms. Section 3 presents the development of the proposed algorithms. Section 4 demonstrates the superior performance of the proposed algorithm. The conclusion is presented in Section 5.

Notation: Throughout the paper, vectors are in boldface and lower case letters, while matrices are in boldface and capital case letters. The transpose and conjugate transpose are expressed by $(\cdot)^T$ and $(\cdot)^H$, respectively. The notation $\text{largest}_s\{A\}$ denotes the sth largest element in a set A; the notation $\otimes$ refers to the Kronecker product. $E[.]$ denotes the expectation operation; the notation $a \sim \chi_b^2$ stands for the case that the variable a has the chi-square distribution with b degrees of freedom. $\mathbf{I}_n$ and $\mathbf{0}_n$ denote the $n \times n$ identity matrix, and the $n \times n$ zero matrix, respectively.

2. Preliminaries

2.1. System models

Suppose the target dynamics can be covered by N possible models at each time step. The state and the measurement equations are

$$\mathbf{x}_{k+1} = \mathbf{A}_k^j \mathbf{x}_k + \mathbf{\Gamma}_k^j \boldsymbol{\upsilon}_k^j, \quad j = 1, \ldots, N,\ k = 0, 1, 2, \ldots \tag{1}$$

and

$$\mathbf{z}_k = \mathbf{H}_k^j \mathbf{x}_k + \boldsymbol{\omega}_k^j \tag{2}$$

where $\mathbf{A}_k^j$ are constant-velocity or maneuvering system matrices; $\boldsymbol{\upsilon}_k^j$ and $\boldsymbol{\omega}_k^j$ are independent zero mean white Gaussian processes. The covariance matrices of process noises are $\mathbf{Q}_k^j = E[(\mathbf{\Gamma}_k^j \boldsymbol{\upsilon}_k^j)(\mathbf{\Gamma}_k^j \boldsymbol{\upsilon}_k^j)^T]$ with $\mathbf{Q}_k^m \neq \mathbf{Q}_k^n$ for $m \neq n$ accounting for slight changes in velocity or fast and slow maneuvers. The covariance matrices of measurement noises are $\mathbf{R}_k^j = E[\boldsymbol{\omega}_k^j (\boldsymbol{\omega}_k^j)^T]$. The model transition process is described using an N-state Markov chain with fixed state transition probabilities p_{ij} satisfying $\sum_{j=1}^N p_{ij} = 1$ for $i = 1, \ldots, N$. The initial state $\mathbf{x}_0$ is assumed to be independent of $\boldsymbol{\upsilon}_k^j$ and $\boldsymbol{\omega}_k^j$.

Remark 1. For convenience, the first model is designated as the constant-velocity model with $\mathbf{Q}_k^1 = \mathbf{0}$ while other models are specified for covering sporadic maneuvers.

2.2. IMM-EV algorithms

Given N models, an integer m with $1 \leq m \leq N$ and model transition probabilities $p_{ij}, i, j = 1, \ldots, N$, the IMM-EV(m) algorithm utilizes the m most likely model paths for combined state estimation. The algorithm is briefly summarized as follows:

- *Initialization*:
  Model probabilities $\mu_0(j)$, updated states $\hat{\mathbf{x}}_0^j$ and state error covariance matrices $\mathbf{P}_0^j$, $j = 1, \ldots, N$ are given.

  $k = 0$

  $k = k + 1$.
- *Calculate mixing probabilities* $\mu_{k-1}(.|j)$:

$$c_j = \sum_{r=1}^{m} \text{largest}_r\{p_{ij}\mu_{k-1}(i) | 1 \leq i \leq N\}, \quad j = 1, \ldots, N,\ s = 1, \ldots, m$$

$$l_{sj} = \arg\{\text{largest}_s\{p_{ij}\mu_{k-1}(i) | 1 \leq i \leq N\}\}, \tag{3}$$

$$\mu_{k-1}(l_{sj}|j) = \frac{\text{largest}_s\{p_{ij}\mu_{k-1}(i) | 1 \leq i \leq N\}}{c_j}. \tag{4}$$

- *Calculate mixed state estimates* $\hat{\mathbf{x}}_{k-1}^{0j}$ *and state error covariance matrices* $\mathbf{P}_{k-1}^{0j}$:

$$\hat{\mathbf{x}}_{k-1}^{0j} = \sum_{s=1}^{m} \mu_{k-1}(l_{sj}|j)\hat{\mathbf{x}}_{k-1}^{l_{sj}}, \quad j = 1, \ldots, N \tag{5}$$

$$\mathbf{P}_{k-1}^{0j} = \sum_{s=1}^{m} \mu_{k-1}(l_{sj}|j)\{\mathbf{P}_{k-1}^{l_{sj}} + [\hat{\mathbf{x}}_{k-1}^{l_{sj}} - \hat{\mathbf{x}}_{k-1}^{0j}] \times [\hat{\mathbf{x}}_{k-1}^{l_{sj}} - \hat{\mathbf{x}}_{k-1}^{0j}]^T\}. \tag{6}$$

- *Kalman filter bank*:
  For $j = 1, \ldots, N$, $\hat{\mathbf{x}}_{k-1}^{0j}$ and $\mathbf{P}_{k-1}^{0j}$ are the inputs to the jth model-based Kalman filtering to yield $\hat{\mathbf{x}}_k^j$, $\mathbf{P}_k^j$, the innovation $\boldsymbol{\nu}_k^j$ with zero mean and covariance $\mathbf{S}_k^j$, the filter gain $\mathbf{W}_k^j$ and the model likelihood function $\Lambda_k(j)$.
- *Update model probabilities* $\mu_k(j)$:

$$\mu_k(j) = \frac{\Lambda_k(j)c_j}{\sum_{r=1}^{N} \Lambda_k(r)c_r}, \quad j = 1, \ldots, N. \tag{7}$$

- *Re-weigh the 'm' largest model probabilities*:

$$\tilde{l}_s = \arg\{\text{largest}_s\{\mu_k(j) | 1 \leq j \leq N\}\}, \quad s = 1, \ldots, m \tag{8}$$

$$\tilde{\mu}_k(\tilde{l}_s) = \frac{\mu_k(\tilde{l}_s)}{\sum_{r=1}^{m} \mu_k(\tilde{l}_r)}. \tag{9}$$

- *Calculate combined state estimate and state error covariance matrix*:

$$\hat{\mathbf{x}}_k = \sum_{s=1}^{m} \tilde{\mu}_k(\tilde{l}_s)\hat{\mathbf{x}}_k^{\tilde{l}_s} \tag{10}$$

$$\mathbf{P}_k = \sum_{s=1}^{m} \tilde{\mu}_k(\tilde{l}_s)\{\mathbf{P}_k^{\tilde{l}_s} + [\hat{\mathbf{x}}_k^{\tilde{l}_s} - \hat{\mathbf{x}}_k][\hat{\mathbf{x}}_k^{\tilde{l}_s} - \hat{\mathbf{x}}_k]^T\}. \tag{11}$$

3. Switched IMM-EV based tracking algorithm

In this section, we propose a tracking algorithm consisting of both the IMM-EV($m = 1$) and the IMM-EV($m = 2$). The algorithm performs three main tasks: constant-velocity tracking, modification of state estimates and maneuver tracking. The IMM-EV($m = 1$) and the IMM-EV($m = 2$) are chosen because as illustrated by Ho and Chen (2006), the former exhibits higher efficiency during target's constant-velocity movements, while the latter yields superior performance during target's maneuvering motions.

3.1. Constant-velocity tracking

The proposed tracking algorithm utilizes the IMM-EV($m = 1$) for quiescence tracking. Meanwhile, it employs a maneuver detection scheme for determining the occurrence and the onset time of a maneuver.

3.1.1. Maneuver detection and onset time estimation

Unlike the maneuver detection schemes of Bogler (1987), Shin and Song (2002) and Willsky and Jones (1976) for system models with exogenous control inputs, the detection method of the vd filter is given for system models without control inputs; therefore, it is appropriate for systems described by (1) and (2). In line with the vd filter, a detection method suitable for the proposed state estimation framework is presented.

Suppose the IMM-EV($m = 1$) is employed at time k with $k > k_c + d + 1$ where k_c denotes the most recent past time at which switching from the IMM-EV($m = 2$) to the IMM-EV($m = 1$)