Int. J. Electron. Commun. (AEÜ) 68 (2014) 130–137

Contents lists available at ScienceDirect

International Journal of Electronics and Communications (AEÜ)

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

Bearings-only maneuvering target tracking based on fuzzy clustering in a cluttered environment

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ARTICLE INFO

Article history:
Received 6 August 2012
Accepted 19 July 2013

Keywords:
Maneuvering target tracking
Fuzzy clustering
IMM
PDAF

ABSTRACT

This paper proposes a novel bearings-only maneuvering target tracking algorithm based on maximum entropy fuzzy clustering in a cluttered environment. In the proposed algorithm, the interacting multiple model (IMM) approach is used to solve the maneuvering problem of target, and the false alarms generated by clutter are accommodated through a probabilistic data association filter (PDAF). To reduce the computational load, the association probability is substituted by fuzzy membership degree provided by a modified version of fuzzy clustering algorithm based on maximum entropy principle, and the "maximum validation distance" is also defined based on the discrimination factor, which enables the algorithm eliminate invalid measurements. Moreover, to avoid the unobservability problem of passive target tracking, a nonlinear measurement model of multiple passive sensors is formulated. Finally, simulation results show that the proposed algorithm has advantages over the conventional IMM-PDAF algorithm in terms of simplicity and efficiency.

1. Introduction

The key to successful maneuvering target tracking in a cluttered environment lies in the effective extraction of useful information about the target's state from observations and dealing with the problem arising from uncertainty about maneuvers target and the uncertain origin of the measurements [1,2]. The underlying statistical model for our problem is a Jump Markov Linear System (JMLS) [3,4], which is a linear system whose parameters evolve with time according to a finite state Markov chain. JMLS are widely used in target tracking. It is well known that the exact computation of conditional mean state estimates involves a prohibitive computational cost exponential in the number of observations.

Several algorithms have been presented in the literature to address this problem, including the probabilistic data association filter (PDAF) algorithm [5], the probabilistic multi-hypothesis tracking (PMHT) algorithm [6], Markov Chain Monte Carlo (MCMC) methods [7], and particle filtering [8,9]. A promising approach is the interacting multiple model (IMM) algorithm, originally developed by Blom and Bar-Shalom [10], which is based on a hybrid system description of the maneuver scenarios, the occurrence of target maneuvers is explicitly included in the kinematics equations through regime jumps. In the presence of clutter, the integration of the IMM and PDAF is an efficient solution to the uncertainty of measurement origins. To compare the performance of different algorithms for tracking highly maneuvering targets in the presence of electronic countermeasures, the PDA-based estimator, in conjunction with the interacting multiple model (IMM) estimator, yielded one of the best solutions [11].

Passive tracking of moving targets using only bearing or line of sight (LOS) angle measurements is a known nonlinear estimation problem. Since the problem is nonlinear, the usual approach for recursive estimation is to employ an extended Kalman filter (EKF) [12]. Because the LOS is an incomplete position observation, it cannot be converted into Cartesian coordinates to allow for linear filtering. In recursive bearings-only tracking, the use of the Cartesian coordinate EKF exhibits erratic estimation results and unstable behavior [13], even without the detrimental effects caused by the presence of false detections or clutter. Furthermore, the azimuth and elevation measurements of a passive sensor do not allow an instantaneous range determination. To solve this problem, two solutions have been considered. First, if the passive sensor platform is allowed to move freely [14], it is possible to recover range observability by selecting an appropriate path for the platform. However, in some applications, the sensor platforms have very slow mobility compared with the target dynamics, so this solution is not feasible. A possible solution is to use several passive sensors and fuse their information in some way to estimate the range.

Dufour and Michel [15] proposed an extended version of IMM-PDAF to track a maneuvering target in three dimensions with two

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http://dx.doi.org/10.1016/j.aeue.2013.07.013

passive sensors in a cluttered environment. The contribution of their work is twofold. First, a novel application of the IMM algorithm is studied, where passive-only sensors are fused for tracking a target maneuvering in three dimensions. Second, several accurate models of target motion are proposed to improve the performance. The main shortcoming of their method is its heavy computational load, particularly in heavily cluttered environments. Recently, we proposed a target tracking method based on maximum entropy fuzzy clustering [16], which has the same performance as PDAF with a lower computational load [17]. Inspired by the literature [16,17], this paper proposes a novel algorithm based on maximum entropy fuzzy clustering for real time maneuvering target tracking.

The remainder of the paper is organized as follows. The problem formulation is presented in Section 2. The maximum entropy clustering algorithm for single target tracking is described and a novel maneuvering target tracking algorithm is introduced in Section 3. Simulation results and performance comparisons with existing algorithms are presented in Section 4. Finally, some conclusions are provided in Section 5.

2. Problem formulation

2.1. System setup

Given a system

$$x^s(k|k) = F^s x^s(k-1|k-1) + v^s(k), \quad k = 1, 2, \ldots \tag{1}$$

$$z_i(k) = h_i(x(k|k)) + e_i(k), \quad i = 1, 2, \ldots l \tag{2}$$

where $x^s(k|k) = (x(k), y(k), h(k), \dot{x}(k), \dot{y}(k), \dot{h}(k))$ is the dynamical state of the system under model s, $x(k)$, $y(k)$ and $h(k)$ denote the Cartesian coordinates of the target, $\dot{x}(k)$, $\dot{y}(v)$ and $\dot{h}(k)$ denote the velocities of target in x, y and h directions, $s \in \{1, 2, \ldots, M\}$ is the model state of the system (e.g., $s = 1$ when the target moves at constant speed and $s = 2$ when the target accelerates). F^s denotes the transition matrix. $z_i(k)$ denotes the measurement from sensor i. The process noise $v^s(k)$ and the measurement noise $e_i(k)$ are independent, zero mean noise vectors with known covariances $Q^s(k)$ and $R_i(k)$, respectively. The mode transition of the system is modeled by a Markov chain with

$$\pi_{ij} = P(s_{k+1} = j \,|\, s_k = i), \quad \forall i, j \in \{1, 2, \ldots, M\} \tag{3}$$

2.2. Target motion models

In this paper, the interacting multiple model approach is used to address the maneuver problem. Three target motion models are used:

Model 1: Constant Velocity Motion

The state transition matrix and the process noise covariance matrix are defined by

$$F^1 = \begin{bmatrix} 1 & 0 & 0 & T & 0 & 0 \\ 0 & 1 & 0 & 0 & T & 0 \\ 0 & 0 & 1 & 0 & 0 & T \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$Q^1 = \begin{bmatrix} \frac{1}{4}T^4 & 0 & 0 & \frac{1}{2}T^3 & 0 & 0 \\ 0 & \frac{1}{4}T^4 & 0 & 0 & \frac{1}{2}T^3 & 0 \\ 0 & 0 & \frac{1}{4}T^4 & 0 & 0 & \frac{1}{2}T^3 \\ \frac{1}{2}T^3 & 0 & 0 & T^2 & 0 & 0 \\ 0 & \frac{1}{2}T^3 & 0 & 0 & T^2 & 0 \\ 0 & 0 & \frac{1}{2}T^3 & 0 & 0 & T^2 \end{bmatrix} \tag{5}$$

Model 2: Constant Turn Motion

The state transition matrix is

$$F^1 = \begin{bmatrix} 1 & 0 & 0 & \frac{\sin(w)}{w} & \frac{\cos(w)-1}{w} & 0 \\ 0 & 1 & 0 & \frac{1-\cos(w)}{w} & \frac{\sin(w)}{w} & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & \cos(w) & -\sin(w) & 0 \\ 0 & 0 & 0 & \sin(w) & \cos(w) & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

where w is a constant angular rate. The process noise covariance matrix is the same as in Model 1.

Model 3: For $w > 0$ describes a clockwise turn, and Model 3 is its natural counterpart for a counterclockwise turn $w < 0$.

3. Proposed maneuvering target tracking method

3.1. Maximum entropy fuzzy clustering

To be specific, suppose that an N-point data set $\{x_i, i = 1, 2, \ldots, N\}$ is related to one of c clusters $\{c_j, j = 1, 2, \ldots, c\}$. The fuzzy clustering process can be formulated as an optimization problem, with the corresponding cost function to be minimized defined as

$$E = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij} d(x_i, c_j) \tag{7}$$

where $d(x_i, c_j)$ is the squared Euclidean distance between the given data point x_i and the cluster center c_i. The probabilistic constraint is that the summation of all $u_{ij} (j = 1, 2, \ldots, c)$ must be equal to one, i.e.

$$\sum_{j=1}^{c} u_{ij} = 1 \quad \forall u_{ij} \in [0, 1] \tag{8}$$

Since the sum of the clustered membership of each data point to all cluster centers $u_{ij} (j = 1, 2, \ldots, c)$ is assumed to be equal to one, and the value of the membership is also nonnegative. Consequently, the clustered membership can be viewed as the probability that this data point is clustered by cluster centers, and we can apply the maximum entropy principle to find out the values of the membership. According to the information theory, the maximum entropy principle (MEP) [16] is the most unbiased prescription to choose the values of membership u_{ij} (or probability), for which the Shannon entropy, i.e., the expression

$$H = H(u_{ij}) = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij} \ln(u_{ij}) \tag{9}$$