

An Evolutionary Algorithm for Optimal Tracking Gate Based on Hybrid Encoding

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1 Introduction

Tracking gate is the first step of data association. Appropriate tracking gate is helpful to reduce the number of false correlations and improve the performance of the target tracking algorithm. Data association algorithms has been a topic of extensive study, but there are few studies on tracking gate. Literature review reveals that most related research on tracking gate focuses much more on gate size than the shapes. Several adaptive design approaches have been proposed in [1–4]. In this paper, hybrid coding genetic algorithm is used to the tracking gate parameters optimization, without dependency of prior knowledge.

2 Overview of Tacking Algorithm

2.1 Target Motion Model

This research focuses on maneuvering target tracking, accordingly, Jerk model is adopted. The components of state vector $X = [x, \dot{x}, \ddot{x}, \overset{\cdot\cdot\cdot}{x}]'$, denote respectively the position, velocity, acceleration, and jerk of the target [5]. The model fully considers the jerk of the target, which can better reflect the mobility of the target.

$$X(k+1) = F(k+1, k)X(k) + U(k) \quad (2.1)$$

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The measurement function is:

$$Z_x(k) = H(k)X(k) + W(k) \quad (2.2)$$

where $H(k) = [1, 0, 0, 0]$ is the system measurement matrix, and $W(k)$ is the measurement noise vector, assumed uncorrelated to the process noise.

2.2 Kalman Filtering and Data Association

The Kalman filtering [6] and probabilistic data association algorithm (PDA) [7, 8] are adopted. The prediction covariance and the observation vector can be described as follow:

$$P(k|k-1) = F(k-1)P_x(k-1|k-1)F^T(k-1) + Q(k-1) \quad (2.3)$$

$$\hat{Z}(k|k-1) = H(k-1)\hat{X}(k|k-1) \quad (2.4)$$

The Kalman gain matrix is given by (2.5), while $S_i(k) = H(k)P(k|k-1)H^T(k) + R(k)$.

$$W_{k|k-1} = P_{k|k-1}H_{k|k-1}^T S_{k|k-1}^{-1} \quad (2.5)$$

The estimate function of i -th candidate measurement is:

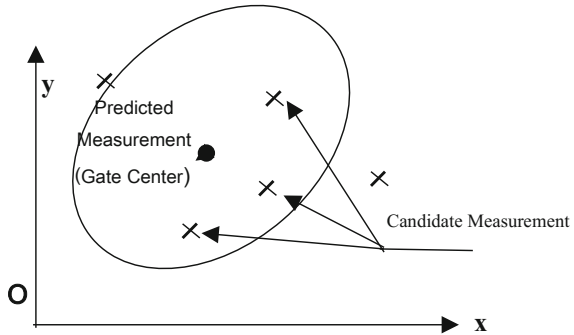
$$\hat{X}_i(k|k) = \hat{X}(k|k-1) + K_i(k)V_i(k) \quad (2.6)$$

Assuming that there are m_k candidate measurements are fall into the gate, after all candidates weighted and association probabilities $\beta_i(k)$ are summed together, the final updated state function can be described as follows:

$$\hat{X}(k|k) = \sum_{i=0}^{m_k} \beta_i(k)\hat{X}_i(k|k) \quad (2.7)$$

where $V(k) = \sum_{i=1}^{m_k} \beta_i(k)V_i(k)$ is combined innovation, $\beta_i(k)$ can be defined as: $\beta_i(k) \triangleq \Pr\{\theta_i(k)|Z^k\}$, where $\theta_i(k) \triangleq \{Z_i(k)\}$, Z^k is the set of candidate measurements up to time k .

Fig. 1 Elliptical gate schematic diagram



2.3 Tracking Gate

The tracking gate is an area by a center point of predicted measurement. It is used to reduce the number of candidate measurements to be considered for further data association [9]. General tracking gates include elliptical gate, rectangular gate and sector gate etc. [10]. If $Z_i(k)$ the i -th measurement at time k meets the following criteria: $D(Z_i(k), \hat{Z}_j(k|k-1)) \leq K_G$, it will be candidate. Where $\hat{Z}_j(k|k-1)$ is the predicted measurement and the gate center point. D is distance function, K_G is the tracking gate constant. Elliptical gate as Fig. 1. The gate size can be tuned by constant K_G , hence K_G can be take as the optimization parameter.

3 Gate Optimization Based on Genetic Algorithm

3.1 Hybrid Encoding

The parameters of tracking gate include shape and size, which are belonged to different data types. Hybrid encoding scheme is applied to ensure both precision and efficiency of algorithm. The gate shapes are represented in binary and the size decoded by float encoding. The individuals contain two components, i.e. $G = [G_S, G_L]$. Where G_S represents shapes, while G_L reflects size. Only rectangular gate and elliptical gate are discussed in this work, set “0” and “1” represent them respectively. Similarly, gate size relates to tracking gate constant which decoded by float encoding [11].

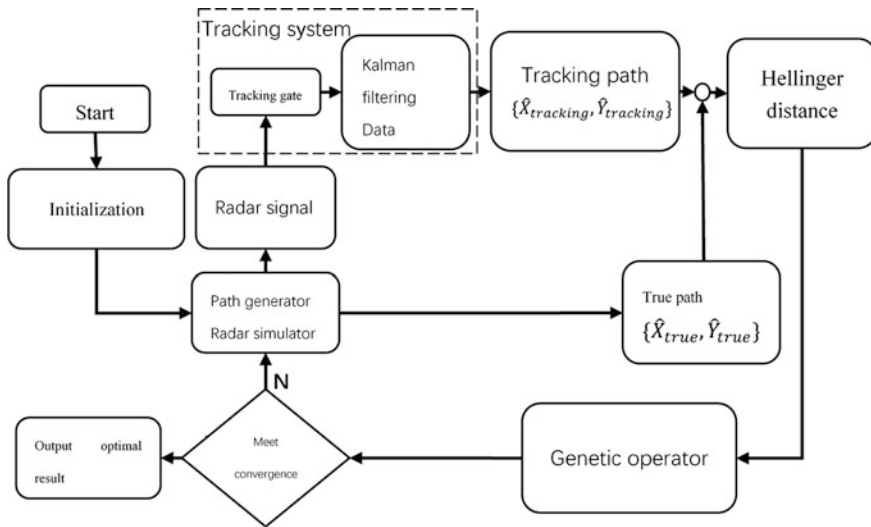


Fig. 2 Flow chart of tracking gate optimization based on hybrid coding genetic algorithm

3.2 Algorithm Description

Obviously, the hybrid encoding genetic algorithm and the tracking system constitute a closed-loop optimization system. Genetic algorithm is adopted for one tache optimization of tracking system, and its optimization objective represents whole system's. The fitness value for genetic operator is more than an algebraic value simply get by arithmetic operations, but obtained by the error of the dynamics tracking system. Therefore, multi-objective optimization problem can be transformed into single-objective problem. This will provide reference for further research of tracking optimization (Fig. 2).

3.3 Hellinger Distance and Fitness Function

There are several metrics currently used to evaluate performance of tracking system, such as position root mean square error (PRMSE), Mahalanobis distance, Hellinger distance, etc. It is difficult to distinguish the true path and the tracking path using PRMSE when the state estimations are same with different uncertainties. Hellinger distance takes more account of covariance to overcome it and has higher appropriate accuracy and sensitivity. It is selected to evaluate the error of the tracking system.

There are two probability distribution $m = N(m, \sum m)$, $n = N(n, \sum n)$ obey Gaussian distribution, Hellinger distance between them is defined as following formula

$$d_H(m, n) = 1 - \sqrt{\frac{\sqrt{\det(\sum m \sum n)}}{\det[0.5(\sum m + \sum n)]}} \exp(\delta) \tag{3.1}$$

Hellinger distance ranging from 0 to 1, which means when the two probability distributions are exactly the same, Hellinger distance get the minimum value of 0. On the contrary, if two sets have no overlapping regions, 1 can be defined as maximum Hellinger distance.

In the tracking system, $m = N(m, \sum m)$ can be regarded as true state vector $\{\hat{X}_{true}(k), \hat{Y}_{true}(k)\}$, where $\sum m$ is uncertainty of true state vector, which can be presented by Cramér-Rao lower bounds $\{P_{true|x}(k), P_{true|y}(k)\}$. $n = N(n, \sum n)$ can be regarded as the estimated state vectors $\{\hat{X}_{tracking|G}(k), \hat{Y}_{tracking|G}(k)\}$ where $\sum n$ represents corresponded error covariance matrix $\{P_{tracking|x,G}(k), P_{tracking|y,G}(k)\}$. Hellinger distance between true path and tracking path can be represented as follows:

$$\begin{aligned} & d_{H|G}(\{\hat{X}_{true}(k), \hat{Y}_{true}(k)\}, \{\hat{X}_{tracking|G}(k), \hat{Y}_{tracking|G}(k)\}) \\ &= 1 - \sqrt{\frac{\sqrt{\det(\{P_{true|x}(k), P_{true|y}(k)\} \{P_{tracking|x,G}(k), P_{tracking|y,G}(k)\})}}{\det[0.5(\{P_{true|x}(k), P_{true|y}(k)\} + \{P_{tracking|x,G}(k), P_{tracking|y,G}(k)\})]}} \exp(\delta) \end{aligned} \tag{3.2}$$

Fitness function is:

$$f_{fitness}(G) = 100 \left(1 - \frac{\sum_{k=0}^t d_{H|G}(\{\hat{X}_{true}(k), \hat{Y}_{true}(k)\}, \{\hat{X}_{tracking|G}(k), \hat{Y}_{tracking|G}(k)\})}{t} \right)^2 \tag{3.3}$$

Accordingly, the optimal tracking gate problem can be transformed into:

$$G = arg_G \max f_{fitness}(G) \tag{3.4}$$

$$\text{s.t. } G = [G_s, G_L] \quad G_s \in \{0, 1\} \quad B_L \leq G_L \leq B_U \quad G_L, B_L, B_U \in R$$

3.4 Genetic Operator

The best individual may be lost at any generation. This can be overcome by employing a heuristic termed elitist selection, which simply always retains the best individual in the population. The population subjected to roulette wheel selection. With this select operator, each chromosome is assigned a probability of being copied into the next generation that is proportional to its fitness relative to all other individual in the population. Successive trials are conducted in which an individual is selected, until all available positions are filled [12].

Two different crossover operators are applied, the bit crossover for binary encoding and the nonuniform arithmetical crossover for float encoding. Similarly, two different encodings also employ the bit mutation and the nonuniform mutation respectively.

4 Simulation Studies

The simulation studies are based on highly maneuvering single target tracking. The initial state of the target is [4.92 km, -79.4 m/s, 0, 0; 0.891 km, 94.6 m/s, 0, 0]. Let an initial population of 20 individuals be selected with the probabilities of crossover and mutation ($P_{crossover} = 0.6$ and $P_{mutate} = 0.01$), respectively. During simulation, the iteration steps are set as 114, sampling interval is 1 s, and the number of simulation is 50. Setting the detection probability as 0.98, the false alarm is generated randomly and uniformly in an area centered on the true measurement. The total number of false alarm is $n_c = \lambda A_v$, λ is the clutter density, A_v is the square of the clutter area. Two scenarios' simulation is given in this research, "light" and "heavy" clutter, with $\lambda = 2$ and $\lambda = 20$ respectively.

Table 1 Statistics table of tracking gate parameter and tracking accuracy

Sparse clutter environment		Dense clutter environment	
Gate parameter	Hellinger distance	Gate parameter	Hellinger distance
Elliptical gate $K_G = 4.217$	0.1782	Elliptical gate $K_G = 6.145$	0.2089
Rectangle gate $K_G = 4.217$	0.1755	Rectangle gate $K_G = 6.145$	0.2024
Elliptical gate $K_G = 4$	0.1790	Elliptical gate $K_G = 7$	0.2059
Elliptical gate $K_G = 5$	0.1776	Elliptical gate $K_G = 5$	0.2129

4.1 Simulation Results and Analysis

With “light” clutter, the parameter converges to 014.217, which means choosing the elliptic gate with gating constant of 4.217 is the optimal result. The Hellinger distance is 0.1708. With “heavy” clutter, the parameter converges to 016.145, optimal tracking gate is elliptic gate too, with gating constant of 6.145 and Hellinger distance is 0.2008.

When the detection probability is given, due to the clutter density increased, the gate size also need to enlarge, the simulation result is in agreement with it. On the other hand, if the tracking gate size is excessively enlarged, it will lead to more false alarms and decreased tracking accuracy. Table 1 shows corresponding tracking accuracy in different cluttered environments and with different tracking gate parameters. Consequently, the proposed tracking gate optimization can ensure high tracking accuracy.

4.2 Discussion About Adaptability of Tracking Gate Optimization

In practical, the disturbances are variable. In this section, simulation studies to test the adaptability of variable disturbances. Apply the optimal result which obtained with clutter density of 20 to the scenario with different clutter density. There is only

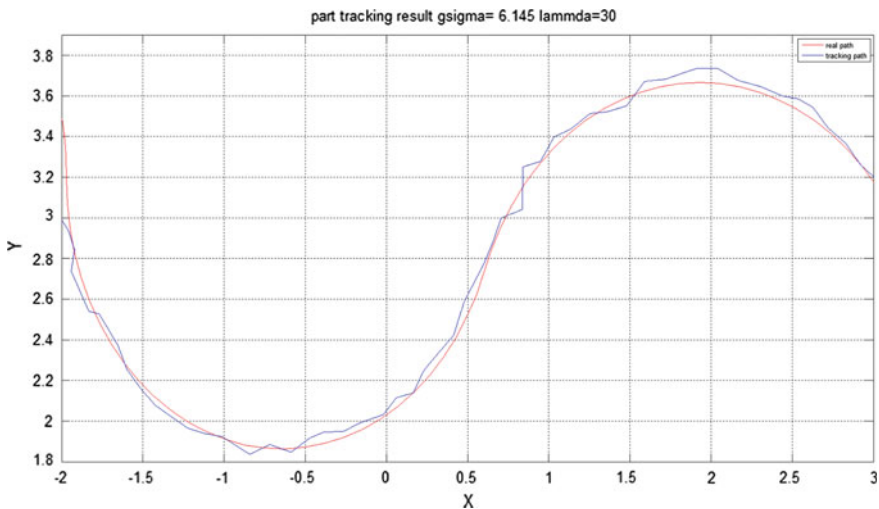


Fig. 3 Tracking with clutter density of 30

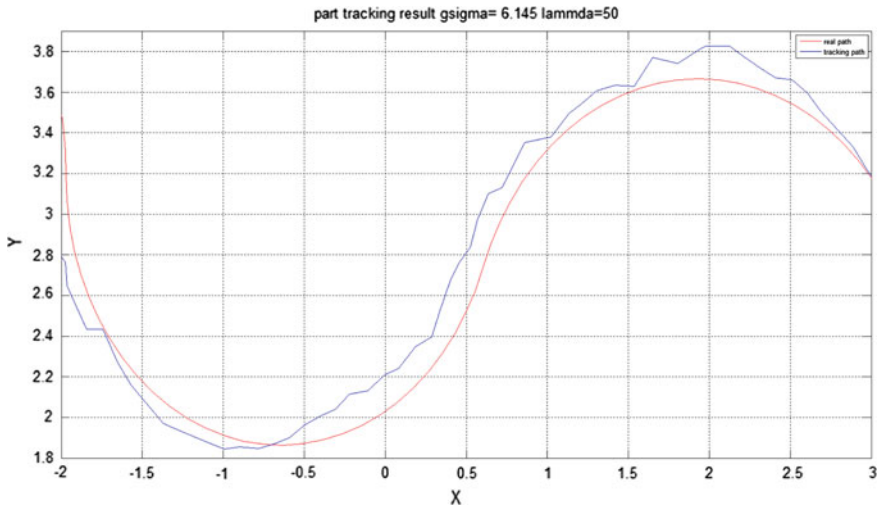


Fig. 4 Tracking with clutter density of 50

a little inconsistency between the truth path and the tracking path with clutter density 30, shown as Fig. 3. With the clutter density increase to 50, obvious deviation is appeared, especially in high maneuvering such as the target makes a bend, shown as Fig. 4.

5 Conclusion

A hybrid encoding genetic algorithm is proposed for the tracking gate optimization in this work. Simulation proved that this algorithm presented prospective tracking performance. Also, certain adaptability can assure during disturbances.

There are still many other factors correlated to the tracking performance, from fine-grain perspective, such as maneuvering frequencies, measurement noise, process noise etc., from coarse-grained viewpoint, there are data association algorithms, maneuvering models, filtering algorithms etc. Obviously, further research can focus on other tracking optimization. In addition, the optimal value is off-line obtained of single target in this paper. How to achieve real-time optimization of multi-target tracking system is also another issue need to be explored.

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