Vol. 16 No. 3 CHINESE JOURNAL OF AERONAUTICS August 2003

FGAs-Based Data Association Algorithm for Multi-sensor Multi-target Tracking

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Abstract: A novel data association algorithm is developed based on fuzzy genetic algorithms (FGAs). The static part of data association uses one FGA to determine both the lists of composite measurements and the solutions of m-best S-D assignment. In the dynamic part of data association, the results of the m-best S-D assignment are then used in turn, with a Kalman filter state estimator, in a multi-population FGA-based dynamic 2D assignment algorithm to estimate the states of the moving targets over time. Such an assignment-based data association algorithm is demonstrated on a simulated passive sensor track formation and maintenance problem. The simulation results show its feasibility in multi-sensor multi-target tracking. Moreover, algorithm development and real-time problems are briefly discussed.

Key words: multi-target tracking; data association; FGA; assignment problem; Kalman filter

一种基于模糊遗传算法的多传感器多目标跟踪数据关联算法. 朱力立, 张焕春, 经亚枝. 中国航空学报(英文版), 2003, 16(3): 177-181.

摘 要: 基于模糊遗传算法发展了一种新的数据关联算法。数据关联的静态部分靠一个模糊遗传算法来得出量测组合序列和 S-D 分配的 m 个最优解。在数据关联的动态部分, 将得到的 S-D 分配的 m 个最优解在一个基于多种群模糊遗传算法的动态2D 分配算法中依靠一个卡尔曼滤波估计器估计出移动目标各个时刻的状态。这一基于分配的数据关联算法的仿真试验内容为被动式传感器的航迹形成和维持的问题。仿真试验的结果表明该算法在多传感器多目标跟踪中应用的可行性。另外, 对算法发展和实时性问题进行了简单讨论。

关键词: 多目标跟踪; 数据关联; 模糊遗传算法; 分配问题; 卡尔曼滤波器
文章编号: 1000-9361(2003)03-0177-05 中图分类号: V243 文献标识码: A

The multi-target tracking problem can be divided into two interrelated tasks of state estimation and data association. Association is the decision process linking observation of a common origin in the presence of false alarms and missed detections. For centralized fusion, static (quasi-state) association (measurements-to-measurements) is used for track formation and generation of the composite measurements for track maintenance, and dynamic association is used for track maintenance[1].

In recent years, multidimensional (*i.e.* S-D) assignment algorithms[1-4] were shown to be effective in data association for multisensor multitarget tracking in the presence of clutter. In assignment, the data association is formulated as the constrained combinatorial optimization problem. However, the S-D assignment problem (either a static one or a dynamic one) is known to be NP-hard[2, 3]. Then the successive Lagrangian relaxation technique[2, 5] was developed to construct suboptimal solutions with pseudo-polynomial complexity. In addition, m-best assignment algorithms[6, 7] obtain top m best assignment solutions by repeatedly using the standard S-D assignment algorithm. A standard genetic algorithm (GA) based static data association (for standard S-D assignment) was proposed in the presence of missed detections only[8].

Received date: 2003-01-13; Revision received date: 2003-04-25
Article URL: http://www.hkxb.net.cn/cja/2003/03/0177/

The focus of this paper is to present an FGAs-based multidimensional assignment algorithm that the authors developed. One modified fuzzy GA (FGA) can obtain m-best S-D assignment solutions in one run. One modified multi-population FGA has the potential of efficient implementations of a suboptimal Multiple Hypothesis Tracking (MHT). Moreover, this algorithm is essentially a combination maximum likelihood (ML) approach.

1 Problem Formulation

The problem formulation follows the work[1-7] of Bar-Shalom and his co-workers. Now briefly describe the problem formulation in this section, and omit detailed exposition. Furthermore, the problem formation discussed here is applicable to tracking problems with synchronized sensors and low speed targets.

1.1 Static assignment problem

The static assignment problem considered in this work is a modified version of the one[1-5] in the literature. The major difference is that the latter must be divided into two parts of the S-D assignment and the m-best S-D assignment, while the former is a whole.

In a multisensor-multitarget scenario[1, 2, 6, 7], there are S lists of measurements from S sensors which are synchronized and provide lists at discrete time samples $t = 1, \cdots, T$. For the static assignment problem, the goal is to associate the S lists of n_s measurements obtained at time instant t, $s = 1, \cdots, S$, which is S dimensions. During the course of implementation, the m-best assignments are determined and ranked in order of increasing cost. The generalized S-D assignment problem is[2, 6, 7]

$$\min_{\rho} \sum_{i_1=0}^{n_1} \cdots \sum_{i_s=0}^{n_s} c_{i_1 \cdots i_s} \rho \tag{1}$$

where $c_{i_1 \cdots i_S}$ is the cost of associating the S-tuple of measurements $(i_1, \cdots, i_s)$, $i_s = 1, \cdots, n_s$. ρ is a binary indicator variable indicating the association of this S-tuple. Note that, in Eq. (1), $i_s = 0$ is a dummy measurement from a list with the consideration of missed detection. The cost (negative logarithm of the generalized likelihood ratio) is[2, 6, 7]

$$c_{i_1 \cdots i_s} = \sum_{s=1}^{S} \Big\{ (u(i_s) - 1) \ln(1 - P_{D_s}) - u(i_s) \ln\left(\frac{P_{D_s} \Psi_s}{\left| 2\pi \boldsymbol{R}_s \right|^{\frac{1}{2}}} \right) + \frac{u(i_s)}{2} \cdot \{ [\boldsymbol{Z}_{si_s} - \hat{\boldsymbol{X}}_p]^{\mathrm{T}} \boldsymbol{R}_s^{-1} [\boldsymbol{Z}_{si_s} - \hat{\boldsymbol{X}}_p] \} \Big\} \tag{2}$$

where Ψ_s is the volume of the field of view of sensor s and $u(i_s)$ is a binary indicator function. $\hat{\boldsymbol{X}}_p$ is the ML state estimation of true target p (here, the conversion of coordinates[1, 2, 6, 7] is omitted for simplification). $\boldsymbol{Z}_{si_s}$ is one measurement originated from p, and is modeled as $\hat{\boldsymbol{X}}_p$ plus additive white Gaussian noise $N(0, \boldsymbol{R}_s)$. Moreover, P_{D_s} is the non-unity detection probability of sensor s.

To determine the m-best assignments, one only need to rank the S-D assignment solutions in order of increasing cost (different from the way in the literature[1, 3, 6, 7]). Define the m-best assignments in the feasible solution space with the m least costs as: $a_1, \cdots, a_m$, with their costs of the assignment (or hypothesis) $c(a_1), \cdots, c(a_m)$, respectively.

1.2 Dynamic 2D assignment problem

The dynamic problem is solved[1, 6, 7] after each scan to update the tracks, starting with the second scan. The goal is to associate the t-th list of composite measurements with the list of tracks formed at time instant $t-1$. According to a second-order kinematic model, the target state[1, 7] is

$$\boldsymbol{X}(t) = \boldsymbol{\Phi}(t, t-1)\boldsymbol{X}(t-1) + \boldsymbol{G}(t-1)\boldsymbol{W}(t-1) \tag{3}$$

where $\boldsymbol{\Phi}(\cdot)$ is the state transition matrix, and $\boldsymbol{G}(\cdot)$ is the disturbance matrix. The process noise vector $\boldsymbol{W}(\cdot)$ is modeled as a white, zero-mean Gaussian random variable with known covariance matrix $\boldsymbol{Q}(\cdot)$. The composite measurements are assumed to be a linear function of the target state corrupted by measurement noise[1, 7],

$$\boldsymbol{Z}(t) = \boldsymbol{H}(t)\boldsymbol{X}(t) + \boldsymbol{V}(t) \tag{4}$$

where $\boldsymbol{H}(\cdot)$ is the measurement matrix, and $\boldsymbol{V}(\cdot)$ is zero-mean white measurement noise with known covariance matrix $\boldsymbol{R}(\cdot)$.

Denote the number of composite measurements corresponding to $a_1, \cdots, a_m$ by $\lambda_1, \cdots, \lambda_m$, respectively. Let $k = 1, \cdots, m$. Define the true measurement probability[7] by

$$P\{z\} = \frac{\sum_{k=1}^{m} d_{zk} \exp(c(a_1) - c(a_k))}{\sum_{k=1}^{m} \exp(c(a_1) - c(a_k))} \quad (5)$$

where d_{zk} is 1, if $z \in a_k$. Otherwise, d_{zk} is zero.

Let y_i, $i = 0, \cdots, N$, denote one track from the track list with the time stamp $t-1$. The solution of the $2D$ assignment problem can be divided into two phases:

Phase 1: m minimization costs and their measurement-track pairs,

$$\{c_{y_i z_j}\} = \begin{cases} \min \sum_{i=0}^{N} \sum_{j=0}^{\lambda_1} c_{y_i z_j} \chi_{y_i z_j} \\ \vdots \qquad \vdots \qquad \vdots \\ \min \sum_{i=0}^{N} \sum_{j=0}^{\lambda_m} c_{y_i z_j} \chi_{y_i z_j} \end{cases} \quad (6)$$

where $\chi_{y_i z_j}$ is a binary assignment variable.

Phase 2: minimization costs for each track from all the corresponding measurement-track pairs, following the results of step 1.

$$\arg \min_{y_i} \{c_{y_i z_j}\} \quad (7)$$

The cost of assigning measurement z_i to track y_i is[7]

$$c_{y_i z_j} = \begin{cases} 0 & \text{if } i = 0 \text{ or } j = 0 \\ -\ln\left(\dfrac{\Lambda(y_i, z_j) P\{z_j\}}{\Lambda(y_0, z_j)}\right) & \text{if } -\ln(\bullet) < 0 \\ \infty & \text{other} \end{cases} \quad (8)$$

where the likelihood function calculation $\Lambda(y_i, z_j)$ from a Kalman filter state estimator is

$$\Lambda(y_i, z_j) = \left[\prod_{k=1}^{t} \left| 2\pi \boldsymbol{S}(k) \right|^{-\frac{1}{2}}\right] \bullet \exp\left[-\frac{1}{2} \sum_{k=1}^{t} \boldsymbol{d}^{\mathrm{T}}(k) \boldsymbol{S}^{-1}(k) \boldsymbol{d}(k)\right] \quad (9)$$

where $\boldsymbol{d}(k)$ is the measurement residual and $\boldsymbol{S}(k)$ is the residual covariance. In addition, the likelihood of false alarms $\Lambda(y_0, z_j)$ is assumed uniformly probable over each sensor's field of view[2, 7], i.e.

$$\Lambda(y_0, z_j) = \prod_{s=1}^{S} \left[\frac{1}{\Psi_s}\right]^{u(i_s)} \quad (10)$$

2 Algorithm Description

The solution approaches adopt FGAs as the fundamental association algorithms. Since the GA is a well-known algorithm, just briefly describe the FGAs here. After that, discuss the assignment algorithm.

2.1 Description of the FGAs

In the literature[9, 10], fuzzy tools or Fuzzy Logic-based techniques are used for modeling different GA components or adapting GA control parameters, respectively, with the goal of improving performance. Generally, GAs resulting from such a way are called Fuzzy GAs (FGAs). Moreover, many research results[9] exhibited the better performance of FGAs, than the standard GAs. An FGA is more efficient than a standard GA in solving the traveling salesman and other combinatorial optimization problems[10]. In preliminary studies, the authors developed an FGA, which adopts 6 fuzzy logic controllers for adapting control parameters (*i.e.* selective pressure, crossover probability and mutation probability) of a modified GA.

2.2 FGA-based static assignment solution

Based on the preliminary studies, the components of the FGA were modified according to the static assignment problem. The main contents will be provided in this subsection.

The chromosome representation is decoded as a symbol string. The alleles are the serial number of measurements corresponding to the targets detected by a sensor. Each chromosome is one list of measurement from one sensor. S chromosomes make an individual. Thus, the genotypes are uniquely mapped onto the S lists of measurements from S sensors. The virtue of such a representation is that it is fit for any measurement data type. The length of each chromosome is equal to the maximum length of the measurement lists. For a short list, one can use dummy measurements to fill it. Generally, the S lists of raw measurements include many efficient association modes. Hence, the initial population is achieved by copying the individual, which denotes the raw measurements (S lists). Moreover, a generation gap is adopted as the Elitist Model for the same reason.

The goal of the assignment algorithm is to globally minimize the cost (see Eq.(1)). To ensure that the resulting fitness values are non-negative, individuals are assigned fitness according to their rank in the population rather than their raw performance. Thus, a selective pressure is used to limit the reproductive range. The selection method is Stochastic Universal Sampling with minimum spread and zero bias. The crossover operation is Partly Mapping Crossover for symbolic code series. The mutation operation is Randomly Two-Point Interchange Mutation for transposition representation of combinatorial optimization problems. The stop criterion of the FGA is a maximum generation number.

The FGA-based static assignment algorithm identifies the targets and estimates their states by ML estimation. It searches a population in parallel by probabilistic transition rules. Only the cost function and corresponding fitness levels directly influence the directions of search. It is important to note that such an algorithm provides a number of potential solutions to the given problem. Hence, one can choose the final solution by ranking the objective association cost. Furthermore, one can select m best association solutions simultaneously for the m-best assignment without repeating run.

2.3 FGA-based dynamic assignment solution

The FGA in the dynamic assignment algorithm is a symbolic coded multi-population FGA. The genetic operation of this FGA is similar to the one discussed in the previous subsection. Moreover, the stop criterion is the same. The difference is the population number and the individual meaning.

Before implementing the dynamic $2D$ assignment algorithm, Eq.(5) is used to select the composite measurements and calculate their probabilities. The selection discards those composite measurements with their probabilities less than a certain threshold. Denote the number of selected composite measurements corresponding to $a_1, \cdots, a_m$ by $\lambda_1', \cdots, \lambda_m'$, respectively. Let $k = k' = 1, \cdots, m$.

The same technique is applied to form all m subpopulations corresponding to $a_1, \cdots, a_m$. The alleles of a particular chromosome k are the serial number of λ_k' composite measurements in a_k. The alleles of a particular chromosome k' are the serial number of tracks to be associated (*i.e.* N tracks). The length of chromosomes k and k' is the big one between λ_k' and N. Dummy measurements or dummy tracks are used to keep $\lambda_k' = N$. Chromosome k and k' make an individual. Thus, the genotypes are uniquely mapped onto measurement-track pairs. The initial population is achieved by copying the individual.

Once the m subpopulations have been built, one can then be ready to track maintenance. Each subpopulation assigns λ_k' composite measurements (from the latest scan) to the N most likely previous tracks using its global cost minimization function in Eq.(6). Specially, $\lambda_1', \cdots, \lambda_m'$ should replace $\lambda_1, \cdots, \lambda_m$. After the preset generation number, all subpopulations yield their measurement-track pairs with the best fitness level. A decision rule Eq.(7) is then used to yield the updated tracks.

Specially, in this approach, the track initiation rule and the track maintenance rule are defined as follows. A new track can be born after two successive scans with measurements assigned to the track. An old track can be eliminated after three successive scans with no measurement assignment to the track.

3 Presentation of Simulation

In this section, a simulated passive multi-sensor multi-target tracking problem is solved with this FGAs-based data association algorithm. The goal is to estimate the feasibility of this algorithm.

The problem is a 7 sensors 5 targets scenario. The simulated measurement data set includes 10 time samples of measurements from 7 sensors. For more details on this scenario, *e.g.* targets simulation and passive sensor specification, see Ref. [7, 9]. This scenario results in very complex candidate associations, in the presence of false alarms and missed detections[3,7,9].

The preset parameters of the algorithm are the following.

For the FGA-based static assignment phase, the population size is 80, the generation gap is 0.6, and the stop generation is 150. 20 best solutions are selected from the S-D assignment results. The selective pressure and the probability of mutation and crossover are adaptive controlled by the FGA.

For the FGA-based dynamic 2-D assignment phase, the number of subpopulations is 20. For each subpopulation, the population size is 40, the generation gap is 0.9, and the stop generation is 50. Each subpopulation has its selective pressure, the probability of mutation and crossover.

Fig. 1 shows the experiment results. These results are similar to those results in Ref. [7]. This denotes the feasibility of this algorithm in such a simulated scenario, although this scenario is simple for state estimation (for the target motion models were constant velocity[7]).

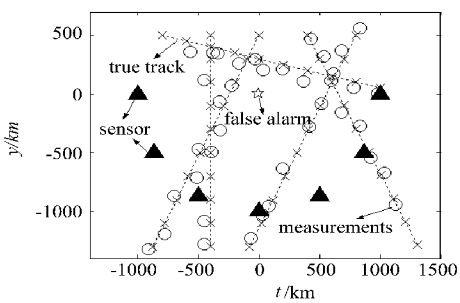

Fig. 1 Tracking results

4 Conclusions

An FGAs-based data association algorithm for multi-sensor multi-target tracking is developed in this paper, and either the FGAs or the m-best S-D assignment technique is modified. The feasibility of the algorithm was demonstrated using a passive multi-sensor multi-target tracking problem. Due to the limited testing in the present work, the algorithm requires further analysis and testing, using both simulated and real multi-sensor multi-target data.

Although the algorithm has shown its feasibility, its practicality seems to be hampered because of the real-time problem. Generally, there are two ways to solve the real-time problem, *i.e.* parallel algorithm and hardware-type algorithm. The latter way is adopted. Design of hardware-type FGA is presently underway, and design of the hardware-type state estimator is planned for future works.

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