레이더 응용을 위한 다중표적 추적 연구

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A Study of Multi-Target tracking for Radar application

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Abstract

This paper introduced a scheme for finding an optimal association matrix that represents the relationships between the measurements and tracks in multi-target tracking of Radar system. We considered the relationships between targets and measurements as MRF and assumed a priori of the associations as a Gibbs distribution. Based on these assumptions, it was possible to reduce the MAP estimate of the association matrix to the energy minimization problem. After then, we defined an energy function over the measurement space, that may incorporate most of the important natural constraints.

1. Introduction

The primary purpose of a multi-target tracking (MTT) system is to provide an accurate estimate of the target position and velocity from the measurement data in a field of view. Naturally, the performance of this system is inherently limited by the measurement inaccuracy and source uncertainty which arises from the presence of missed detection, false alarm, emergence of new targets into the surveillance region and disappearance of old targets from the surveillance region. Therefore, it is difficult to determine precisely which target corresponds to each of the closely spaced measurements. Although trajectory estimation problems have been well studied in the past, much of this previous work assumes that the particular target corresponding to each observation is known. Recently, with the proliferation of surveillance systems and their increased sophistication, the tools for designing algorithms for data association have been announced.

In this paper, we derive the new model for data association which reflects the natural constraints of the MTT problem and convert the derived model into the minimization problem of energy function by MAP estimator [1]. The coefficients of energy function is calculated by Lagrange multiplier,[2] and local dual theory[3].

2. Problem Formulation and Energy Function

Fig.1 shows the overall system which consist of acquisition, association and prediction. Our primary concern is the association part that must determine the actual measurement ad target pairs, given the measurement and the predicted gate centers.

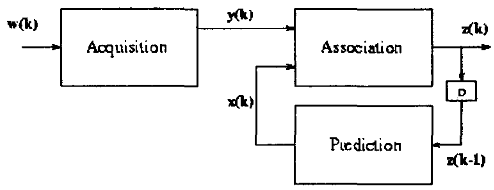

Fig. 1. An overall scheme for target tracking

Let m and n be the number of measurements and targets, respectively, in a surveillance region. Then the validation matrix w [3] is :

$$\omega = \{\omega_{jt} \mid j \in [1, m], t \in [0, n]\} \tag{1}$$

where the first column denotes clutter and always w_{jo}. Based on the validation matrix, we must find hypothesis matrix[4], $\hat{\omega}(=\{\hat{\omega}_{jt} \mid j \in [1,m], t \in [0,n]\})$ that must obey the following natural constraints:

$$\begin{cases} \sum_{t=0}^{n} \hat{\omega}_{jt} = 1 \quad for \quad (j \in [1,m]) \\ \sum_{j=1}^{m} \hat{\omega}_{jt} \le 1 \quad for \quad (t \in [1,n]) \end{cases} \tag{2}$$

$\hat{\Omega}$ The ultimate goal of this paper is to find the hypothesis matrix given the observation **y** and **x**, which must satisfy (2). Let's associate the realizations the gate center x, the measurement y, the validaton matrix w, and $\hat{\omega}$ - to the random processes $X,Y,\Omega,$ and $\hat{\Omega}$.

Next, consider that $\hat{\Omega}$ is a parameter space and $X,Y,\Omega,$ is an observation space. Then a posteriori can be derived by the Bayes rule:

$$P(\hat{\omega} \mid \omega,y,x) = \frac{P(\omega \mid \hat{\omega})P(y,x \mid \hat{\omega})p(\hat{\omega})}{P(\omega,y,x)} \tag{3}$$

We assume the parameter $\hat{\Omega},\Omega$ are given and (X,Y) are observed. If the conditional probabilities describing the relationships between the parameter space and the observation spaces are available, one can obtain the MAP estimator:

$$\hat{\omega}^{*} = \arg\max_{\hat{\omega}} P(\hat{\omega} \mid \omega,y,x) \tag{4}$$

As a system model, we also assume that the conditional probabilities are all Gibbs distributions:

$$\begin{cases} P(y,x \mid \hat{\omega}) \equiv \frac{1}{Z_1}\exp\{-E(y,x \mid \hat{\omega})\} \\ P(\omega \mid \hat{\omega}) \equiv \frac{1}{Z_2}\exp\{-E(\omega \mid \hat{\omega})\} \\ P(\hat{\omega}) \equiv \frac{1}{Z_3}\exp\{-E(\hat{\omega})\} \end{cases} \tag{5}$$

where i $Z_s(s \in [1,2,3]$ is called partition function:

$$Z_s = \int_{\hat{\omega}\in\Xi} \exp\{-E(\hat{\omega})\}d\hat{\omega} \tag{6}$$

Here, E denotes the energy function. Substituting (5) into (4), (6) becomes

$$\hat{\omega}^{*} = \arg\min x_{\hat{\omega}}[E(y,x \mid \hat{\omega}) + E(\omega \mid \hat{\omega}) + E(\hat{\omega})] \tag{7}$$

The first term in (7) represents the distance between measurement and target and must be minimized using feasible events. The second term intend to suppress the measurements which are uncorrelated with the valid measurements. The third term denotes constraints of the validation matrix and it can be designed to represent the two restrictions. The energy equations of each term are defined respectively:

$$\begin{cases} E(y,x \mid \hat{\omega}) \equiv \sum_{t=1}^{n}\sum_{j=1}^{m} r_{jt}\hat{\omega}_{jt} \\ E(\omega \mid \hat{\omega}) \equiv \sum_{t=1}^{n}\sum_{j=1}^{m}(\hat{\omega}_{jt} - \omega_{jt})^2 \\ E(\hat{\omega}) \equiv \sum_{t=1}^{n}(\sum_{j=1}^{m}\hat{\omega}_{jt} - 1) + \sum_{j=1}^{m}(\sum_{t=0}^{n}\hat{\omega}_{jt} - 1) \end{cases} \tag{8}$$

Putting (8) into (7), one gets

$$\hat{\omega}^{*} = \arg\max_{\hat{\omega}}[\alpha\sum_{t=1}^{n}\sum_{j=1}^{m} r_{jt}\hat{\omega}_{jt} + \frac{\beta}{2}\sum_{t=1}^{n}\sum_{j=1}^{m}(\hat{\omega}_{jt} - \omega_{jt})^2 + \sum_{t=1}^{n}(\sum_{j=1}^{m}\hat{\omega}_{jt} - 1) + \sum_{j=1}^{m}(\sum_{t=0}^{n}\hat{\omega}_{jt} - 1)] \quad 9$$

where $r_{jt} = (x_j d_{yt} - y_j d_{xt})^2 / (d_{xt}^2 + d_{yt}^2)$, and α and β are parameters of the weighted distance measure and the matching term respectively.

3. Design of Optimal Adaptive Data Association Scheme

The optimal solution for (9) is hard to find by any deterministic method. Instead, one can convert the present constrained optimization problem to an unconstrained problem by introducing Lagrange multipliers ad using the local dual theory[5]. The problem is to find such that where

$$L(\hat{\omega},\lambda,\varepsilon) = \alpha\sum_{t=1}^{n}\sum_{j=1}^{m} r_{jt}\hat{\omega}_{jt} + \frac{\beta}{2}\sum_{t=1}^{n}\sum_{j=1}^{m}(\hat{\omega}_{jt} - \omega_{jt})^2 + \sum_{t=1}^{n}\lambda_t(\sum_{j=1}^{m}\hat{\omega}_{jt} - 1) + \sum_{j=1}^{m}\varepsilon_j(\sum_{t=0}^{n}\hat{\omega}_{jt} - 1) \tag{10}$$

Here, λ and ε are just Lagrange multipliers. Note that (10) includes the effect of the first column of the associated matrix, which represents the clutter as well as newly appearing targets. In general setting, we assume m>n, since most of the multitarget problem is characterized by many confusing measurements that exceed far over the number of original targets.

Since (10) is a convex function which guarantes the extrema, using the convex analysis for the local duality, the optimal solution can be obtained by

$$(\hat{\omega}^*, \lambda^*, \varepsilon^*) = \arg\max_{\varepsilon} \max_{\lambda} \min_{\hat{\omega} \geq 0} L(\hat{\omega}, \lambda, \varepsilon) \tag{11}$$

The necessary condition for achiving extreme in (10) are

$$\begin{cases} \nabla_{\hat{\omega}_{jt}} L(\hat{\omega}, \lambda, \varepsilon) & = & 0 \\ \nabla_{\lambda_t} L(\hat{\omega}, \lambda, \varepsilon) & = & 0 \\ \nabla_{\varepsilon_j} L(\hat{\omega}, \lambda, \varepsilon) & = & 0 \end{cases} \tag{12}$$

Using (12), one obtains the final representations of the solution:

$$\begin{cases} \hat{\omega}^*_{jt} & = & \{\beta\omega_{jt} - \alpha r_{jt}(1-\delta_t) - \lambda_t - \varepsilon_j\}/\beta \\ \lambda^*_t & = & -\frac{\beta}{m}(1 + d_{mn}\delta_t) - \frac{1}{m}\sum_{j=1}^{m} f_{jt}(\varepsilon_j) \\ \varepsilon^*_j & = & \bar{\varepsilon}^{\tau}_j + \mu[\frac{1}{n+1}\sum_{t=0}^{n}\{\beta(\omega_{jt} - \bar{\omega}_t) - \alpha(1-\delta_t)(r_{jt} - \bar{r}_t)\}] \end{cases}$$

(13)

which ε means optimal value of $\bar{\varepsilon}$ at any scan.

(13) contains two parameters α and β. To obtain these parameters, we consider the ML(maximum likelihood) estimation: Given (w, y, x), Θ is estimated as a maximum likelihood estimate such that

$$\Theta = \arg\max_{\Theta} P(\omega, y, x \mid \hat{\omega}, \Theta) \tag{14}$$

where $\Theta \equiv [\alpha \mid \beta]^T$. Unfortunatley, although the ML is unique if it exists, the ML estimation is computationally prohibitive due to the calculation of the partition function. Therefore, as an alternative of ML, MPL(Maximum Pseudo Likelihood) is considered. In the MPL estimation, $P(\omega, y, x \mid \hat{\omega}, \Theta)$ is represented as a product of local partition function:

$$P(\omega, y, x \mid \hat{\omega}, \Theta) = \frac{P(y, x \mid \omega, \hat{\omega}, \Theta) P(\hat{\omega} \mid \omega, \Theta) P(\omega \mid \Theta)}{P(\hat{\omega} \mid \Theta)}$$
$$= \prod_{t=0}^{n} \prod_{j=1}^{m} \tfrac{1}{Z_{jt}} \exp\{-\Theta^T \Phi(\hat{\omega}_{jt})\}$$

(15)

where Z_{jt} is a local partition function:

$$Z_{jt} = \sum_{\hat{\omega}_{jt} \in \hat{\omega}} \exp\{-\alpha r_{jt}\hat{\omega}_{jt}\delta_t - \tfrac{\beta}{2}(\hat{\omega}_{jt} - \omega_{jt})^2] \tag{16}$$

and cost function $\Phi(\hat{\omega}_{jt})$ is

$$\Theta(\hat{\omega}_{jt}) = \begin{bmatrix} r_{jt}\hat{\omega}_{jt}\delta_t \\ \tfrac{1}{2}(\hat{\omega}_{jt} - \omega_{jt})^2 \end{bmatrix} \tag{17}$$

It is proven that (16) is strictly concave with respect to Θ if and only if the parameters that comprise Θ are linearly independent with each other. Therefore, Θ can be found from the gradient search method:

$$\frac{\partial \Theta}{\partial t} = -\mu \nabla_{\Theta} \log P(\omega, y, x \mid \hat{\omega}, \Theta) \tag{18}$$

Putting (15) into (18) arrives

$$\Theta^{\tau+1} = \Theta^{\upsilon} - \mu \nabla_{\Theta} \ln P(\omega, y, x \mid \hat{\omega}, \Theta)|_{\Theta = \Theta^{\tau}}$$
$$= \Theta^{\upsilon} - \mu \sum_{t=0}^{N}\sum_{j=1}^{N}[\Phi(\hat{\omega}_{jt}) - \tfrac{1}{Z_{jt}} \sum_{\hat{\omega}_{jt} \in \hat{\omega}} \Phi(\hat{\omega}_{jt}) \exp(-\Theta^{\tau^T} \Phi(\hat{\omega}_{jt}))]$$

(19)

where μ and τ are an updating constant and an iteration index, respectively.

In fig. 2, we show the overall computational flow structure. Its structure consists of the two parts: data association and parameter updating. The data association block transforms the input data into the energy equation to obtain the feasible matrix. Inside the block, first is calculated and then . Finally, feasible matrix, will be calculated. The parameter estimation block updates the parameter using the previous input and feasible matrix data.

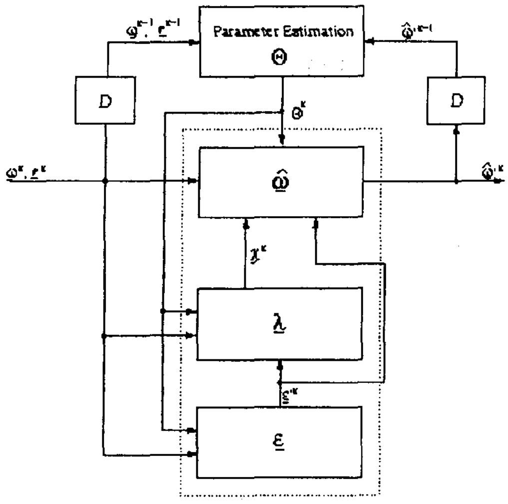

Fig.2. Overall flow diagram of optimal data association algorithm

According to the overall computational flow structure, the computational complexity analysis is simplified as numbers of multiplications in data association and parameter updating. Suppose that there are n targets and m measurements. And assume that the average iteration number of ε_j and λ_i is $\bar{k}_1$ and $\bar{k}_2$, respectively. In this case, λ and ε's computation in the data association stage require and . The necessary computation of the feasible matrix extractions is multiplications. Therefore the number of multiplications required in the data association part is $O((\bar{k}_1 + \bar{k}_2 + 1)mn)$.

4. Conclusion

In this paper, we have developed the optimal adaptive data association scheme for radar multi-target tracking system. This scheme is designed to determine all parameters automatically and requires multiplications. We have confirmed that all parameters converge to steady states in the data association capability simulation and tracking accuracy is superior to that of JPDA about 5.2% in view of tracking accuracy under the clutter density of c=0.4. The superiority of this scheme to the JPDA comes from two important points. At first, this scheme used course weighted distance compared to the averaged weighting distance of JPDA. Under the heavy clutter ambient, target's direction is more important than the correct position. The second is that the new algorithm can reject the irrespective plots from the validation matrix by incorporating the matching term in the energy equations.

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