Combining of IMM filtering and DS data association for multitarget tracking

Hongshe Dang
School of Electrical&Electronics
Shaanxi Science&Technology University
Xianyang, Shaan xi 712081, P. R. China
hsdang@sohu.com

Chongzhao Han
Institute of Synthetic Automation
Xi'an Jiaotong University
Xi'an, Shaan xi 710049, P. R. China
czhan@mail.xjtu.edu.cn

Dominique GRUYER
Laboratoire sur les Interactions Véhicules, Infrastructure, Conducteurs 14, Route de la minière – Satory, 78000 Versailles – France
dominique.gruyer@inrets.fr

Abstract – *The tracking of targets in road situation represents a challenge for both the measurement to track association and the positional estimation algorithms. Previous simulation have shown that the data association method based on evidence theory has a good performance, compared with the Nearest Neighbor (NN) and cheap JPDAF method, moreover it has proved that the Interacting Multiple Models (IMM) method has a superior tracking performance than other state estimators. So in this paper, the IMM method and the data association method based on evidence theory were integrated into one algorithm. Monte Carlo simulation results indicate that the new method has a high tracking accuracy.*

Keywords: Multi-target tracking, data association, evidential combination, IMM (interacting multiple model).

1. Introduction

With the increasing number of road vehicles, many security problems are appear, and the safety problems become more important, it is necessary to develop collision warning/avoidance (CW/CA) system or adaptive cruise control (ACC) systems to protect the drivers and vehicles. Ensure the accurate tracking of multiple vehicles (targets) present in the environment are the main content of CW/CA or ACC systems.

State estimation and data association are the two main stages of the target tracking, Without a good association, state estimation is at risk, and without a good state estimation, the association may be useless.

Many data association method such as Nearest Neighbour(NN), MHT, JPDA etc were proposed, In a previous paper[3], Gruyer proposed a data association method based on Dempster-Shafer theory, and compared with the Nearest Neighbour(NN), the new method can get a high percent of perfect correlation.

Non-manoeuvring targets can be accurately tracked with a constant velocity(CV) filter, however the quality of the position and velocity estimates might be degraded significantly when a target manoeuvres, since the CV filter couldn't match with the manoeuvres motion. In recent years, various tracking filters for manoeuvering target have been studied. The interacting multiple model state estimators(IMM)[2], in which multiple filters are operated in parallel and integrated by their mode of probabilities, provides a better tracking accuracy for manoeuvering targets than obtained from other single-scan positional estimators such as the Kalman filter or more complexes estimators making use of rule-based manoeuver detectors.

The IMM is expected to reduce tracking errors for both non-manoeuvering and manoeuvering target. However the IMM requires heavy computational load, because it uses multiple Kalman filters in parallel.

Vehicles on road generally have two basic motion modes, These modes are the uniform motion and the manoeuver. The first one refers that the vehicles have a constant speed motion, the second one refers that the vehicles have a starting, a stopping or a turning motion. So the tracking system must take into account the situation that the target are running.

In this paper, the IMM state estimation method and the D-S data association method are together in order to track vehicles or targets in road situation. The simulation result proves that the new method has a good performance.

The paper is organized as follows. Section 2 introduces the data association method based on DST; section 3 Interacting Multiple Models (IMM) method; section 4 gives the realization of the proposed method; In the section 5, the simulation results are presented; and the section 6 gives the conclusion.

2. The data association method based on DS theory

Recently people working in the fusion of uncertain data have been interested in the Dempster-Shafer theory essentially because (1) it is a nice and flexible way to represent uncertainty, from the total ignorance toward any form of partial or total knowledge, that is more general than what the probabilistic approach provides, and (2) secondly, this theory provides a set of rules in order to combine uncertain data, The most used rule is called the Dempster's rule of combination, that seems to provide an excellent tool for data-aggregation.

The Dempster's rule of combination synthesizes basic probability assignments from distribution of masses and produces a new synthetic probability assignment representing the combined information. The combination rule is known as the orthogonal sum.

Let m_1 and m_2 be the basic probability assignments, on the same frame of discernment, for belief functions Bel_1 and Bel_2 respectively. The focal elements of Bel_1 are $B_1,...,B_k$ and the focal elements of Bel_2 are $B_1,...,B_k$, the total portion of belief exactly committed to A (A is not an empty set) is given by the orthogonal sum.

$$m(A)=\begin{cases} 0 & A=\phi \\ \sum_{A_i\cap B_j=A} m_1(A_i)m_2(B_j) \big/ 1-k & A\neq\phi \end{cases} \tag{1}$$

$$k=\sum_{A_i\cap B_j=\phi} m_1(A_i)m_2(B_j)\prec 1$$

Where k is called the normalization factor, which is often interpreted as a measure of conflict between the different sources.

In order to treat with the uncertain and inaccuracy of sensor data for rebuilding the environment for intelligent vehicles, Gruyer[3] and Rombaut[4] using Dempster-Shafer theory and fuzzy logic in the data association process to solve the problem of correlation between the tracks (known targets) and the measurements (new targets). This allows firstly to follow the objects temporal evolution and secondly to increase the reliability of environment perception. .

According to the Dempster's rule, the combination result of n mass sets is produced in cascade[3].

$$m_{i,.}(Y_j)=K_{i,.}m_{i,j}(Y_j)\prod_{\substack{k=1...n \\ k\neq j}}(1-m_{i,k}(Y_k)) \tag{2}$$

$$m_{i,.}(*)=K_{i,.}\prod_{j=1...n} m_{i,j}(\overline{Y}_j) \tag{3}$$

$$m_{i,.}(\Theta)=K_{i,.}(\prod_{j=1...n}(1-m_{i,k}(Y_k))-\prod_{j=1...n}m_{i,j}(\overline{Y}_j)) \tag{4}$$

The realizations of data association based on D-S theory are as follows:

Step1 : Calculate the belief matrix $M_{i,.}$ between the measurement vector X and the track vector Y, according to the mass functions.

Step2 : Calculate the belief matrix $M_{.,j}$ between the track vector Y and the measurement vector X, according to the mass functions.

Step3 : Finally decision. The correlation between the measurement vector and the track vector is similarity with the correlation between the track vector and the measurement vector. The matrix $M_{i,.}$ and $M_{.,j}$ can represent the relations between the tracks (known objects) and the measurements (perceived objects). First, a local decision with the matrix $M_{i,.}$ or $M_{.,j}$ was made according to the maximization rule. Then, if the decision from the first matrix is consistent with that of the second matrix, the decision is the finally decision, otherwise the decision is ignored.

3. Interacting Multiple Models (IMM) method

The Interacting Multiple Models estimator is used to predict the current state of the target using two or more different models. For the IMM estimator, multiple state equations are used to describe each of the different modes of operation [2]. A Markov transition matrix is used to specify the probability that the target is in one of the modes of operation. Usually, these values are chosen heuristically. The model probabilities are updated at each new measurement, and the resulting weighting factors are used in calculating the state. One cycle of a practical IMM algorithm consists of the following steps:

Step1. Calculate the mixing probabilities

The probability that mode M_i was in effect at time k-1 given that M_j is in effect at time k conditioned on Z^{k-1} is calculated as :

$$\mu_{i|j}(k-1|k-1)=P\{M_i(k-1)\,|\,M_j(k),Z^{k-1}\} \\ =\frac{1}{\overline{c}_j}p_{ij}\mu_j(k-1) \tag{5}$$

where $\overline{c}_j=\sum_{i=1}^{r}p_{ij}\mu_i(k-1)$ is the predicted mode probabilities.

Step2. Calculate the mixed initial condition

Starting with previous state estimates $\hat{x}^i(k-1/k-1)$ obtained as output from the r different kalman filters(acting as the r different modes), and corresponding covariance matrices $P^i(k-1/k-1)$, a mixed initial condition for the filter M_j at time k is calculated as :

$$\hat{x}^{0j}(k-1/k-1)=\sum_{i=1}^{r}\hat{x}^i(k-1/k-1)\cdot\mu_{i|j}(k-1/k-1) \tag{6}$$

and the corresponding covariance as :

$$P^{0j}(k-1/k-1)=\sum_{i=1}^{r}\mu_{i|j}(k-1/k-1)\cdot\{P^i(k-1/k-1) \\ +\left[\hat{x}^i(k-1/k-1)-\hat{x}^{0j}(k-1/k-1)\right] \\ \cdot\left[\hat{x}^i(k-1/k-1)-\hat{x}^{0j}(k-1/k-1)\right]^T\} \tag{7}$$

Step3. Perform mode-matched filtering and calculate the likelihood functions corresponding to the r filters. Use the estimate $\hat{x}^{0j}(k-1/k-1)$ and the corresponding covariance $P^{0j}(k-1/k-1)$ as inputs to the filter matched to $M_j(k)$, which uses $z(k)$ to yield $\hat{x}^j(k/k)$ and $P^j(k/k)$.

The likelihood functions for filters j is as follows :

$$\Lambda_j(k) = N\left[v_j(k);0,S_j(k)\right] = \left|2\pi S_j(k)\right|^{-\frac{1}{2}} \times \exp\left[-\frac{1}{2}v_j^T(k)S_j^{-1}(k)v_j(k)\right] \quad (8)$$

where $v_j(k)=z(k)-\hat{z}(k|k-1)$ is the innovation for filter j and $S_j(k)$ is the covariance matrix associated with $v_j(k)$.

Step 4. Update mode probability

The new mode probabilities are calculated as follows :

$$\mu_j(k) = \frac{1}{c}\Lambda_j(k)\bar{c}_j \quad (9)$$

where $c = \sum_{j=1}^{r}\Lambda_j(k)\bar{c}_j$ (10)

Step5.Combine model-conditioned estimates and covariance. For output purposes only, $\hat{x}(k|k)$ and $P(k|k)$ are computed according to

$$\hat{x}(k|k) = \sum_{i=1}^{r}\hat{x}^i(k|k)\mu_i(k) \quad (11)$$

$$P(k|k) = \sum_{i=1}^{r}\mu_i(k)\{P^i(k|k) + [\hat{x}^i(k|k)-\hat{x}(k|k)] \cdot [\hat{x}^i(k|k)-\hat{x}(k|k)]^T\} \quad (12)$$

4. Integration of the IMM and DS

The data association problem between the measurement and the tracks in target tracking is really an assignment problem, assigning the measurements to the tracks at time k. In order to reduce the computation complexity, the prediction of the target is used, which is determined by using kalman filter etc. So the purpose of the data association was to assign the measurements x_i (s-dimension vector, $i=1,2,\ldots,n$)to the target predictions y_j (s-dimension vector, $j=1,2,\ldots,m$), the relations between the measurements and the tracks must be determined before the assigning.

As explained above, the IMM algorithm employs the measurement $z(k)$ to be matched with the appropriate track at this time. If we match the measurements with all the individual model estimates, the computation load for data association will increase, especially when the number of targets is big, because there are about two or more model for every targets.

So a suitable mixing of the individual model estimates is required. This is done by introducing the predicted conditional probabilities, which are naturally calculated as:

$$\mu_{i|j}(k|k-1) = P\{M_i(k-1)|M_j(k),Z^{k-1}\} = \frac{1}{c_j}p_{ij}\mu_i(k-1) \quad (13)$$

where $c_j = \sum_{i=1}^{r}p_{ij}\mu_i(k-1)$

The individual modal estimates are now mixed to produce the "aggregated" state and covariance estimates, which identify the tracks for the purpose of measurement to track association.

$$\hat{x}(k|k-1) = \sum_{i=1}^{r}\hat{x}^i(k|k-1)\mu_i(k|k-1) \quad (14)$$

$$P(k|k-1) = \sum_{i=1}^{r}\mu_i(k|k-1)\{P^i(k|k-1) + [\hat{x}^i(k|k-1)-\hat{x}(k|k-1)] \cdot [\hat{x}^i(k|k-1)-\hat{x}(k|k-1)]^T\} \quad (15)$$

Where

$$\hat{x}^j(k|k-1) = F\hat{x}^j(k-1|k-1),\ j=1,\ldots,r \quad (16)$$

$$P^jk|k-1) = FP^j(k-1|k-1)F^T + GQG^T \quad (17)$$

The "aggregated" state and covariance estimates $\hat{x}(k|k-1)$ and $P(k|k-1)$ are used as inputs to the D-S module to produce the desired measurement to track (target) associations. The two modules: IMM filtering and D-S data association method, are then integrated into one algorithm.

5. Realization of the DS-IMM method

The realization of the DS-IMM method can be described as follows:

Step1. Calculate mixing probabilities $\mu_{i|j}(k-1|k-1)$, mixed initial condition $\hat{x}^{0j}(k-1/k-1)$, $P^{0j}(k-1/k-1)$;

Step2. based the conditions at time $k-1$, Compute state predictions $\hat{x}(k/k-1)$ and covariance predictions $P(k/k-1)$ for every target, According (13) to (17) ;

Step3. Using the measurement $z(k)$ at time k and the predictions computed at step2 as inputs to the D-S module to produce the desired measurement to track(target) associations.

Step4. Based the confirmed measurement and the initial conditions, perform mode-matched filtering and calculate the likelihood functions corresponding to the r filters.

Step5.Updating mode probability and calculating model-conditioned estimates $\hat{x}(k|k)$ and covariance $P(k|k)$ for output.

6. Simulation results

Generally, vehicles in road situation have two basic motion models[6] :uniform motion and maneuver. The former refers to the motion that the targets before our vehicle run with a constant speed and can be represented by a near constant velocity model(or white noise acceleration model-WNA) and the latter refers to the motion that the target run in starting, stopping or turning(e.g. overtaking) station. the motion of a vehicle (target) can be modeled with a coordinated turn(CT model), a WNA model or a Singer model(SM) etc.

Following other paper's results and bibliography for vehicle's motion, a variety of combinations can be chosed in order to provide a sufficient tracking performance for the IMM estimator. Such as Two WNA model, A WNA and a CT model, a WNA and a SM modeletc. In this paper, we use two WNA model to realizing the IMM method. The transition matrix is :

$$p = \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix}$$

Simulation studies have been performed in order to compare performance results derived from the DS/IMM system described above with those obtained from a single filter model (SFM) system, which generally was a kalman filter. For simple,suppose there two vehicles are running in a straight line road before self-vehicle, there aren't turning, overtaking etc. The two targets have the same state transition and measurement transition matrixes, the actual trajectories have the constant velocities of 5m/s, and 4m/s, and the initial range is 70m, and 65m[7]. After running as constant velocity for 5 second, the vehicles have a acceleration with the self-vehicle.

The self-vehicle using millimeter wave radar detects the position of targets,which is the real measurement about the target, along with the noisy range and clutter measurements, the deviation of the measurement noise has been selected as $\sigma^2 = 0.5m^2$, and sample interval is $T = 0.1s$.

To evaluate the performance of the proposed method, two criteria were used, one is the Root of Mean Square error, one is the percent of perfect correlation, generally speaking, the two criteria can evaluate the tracking performance accurately. The definition of RMS error is:

$$RMS\_error(k) = \sqrt{\frac{1}{M}\sum_{j=1}^{M}(x(k)-\hat{x}^j(k))(x(k)-\hat{x}^j(k)^T}$$

Where $x(k)$, $\hat{x}^j(k)$ stand for the true state of target and its estimation in the running j th at time k . M is the times of Monte Carlo running.

Fig 1and Fig 2 are the RMS track errors of the DS-SFM and DS-IMM method, for a 50 monte carlo simulation. The blue line is the result of the DS-SFM method, the red line is the result of the DS-IMM method.

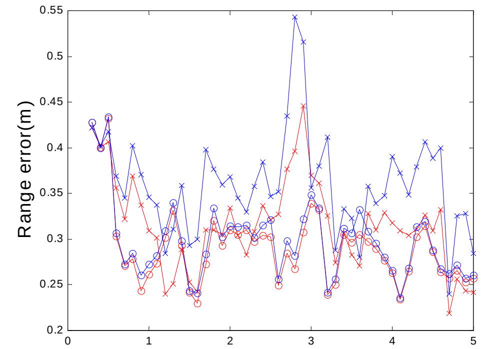

Fig 1. position track errors

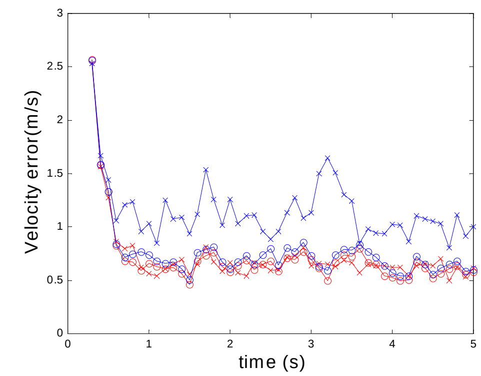

Fig2. velocity track error

Fig3.to Fig4. are the percent of perfect association for different clutter measurement, with Fig3. there is one clutter at every measurement, with Fig4., there is two clutter, with Fig5. there is there clutter. and the clutter is distributed equally in the measure range of sensor.

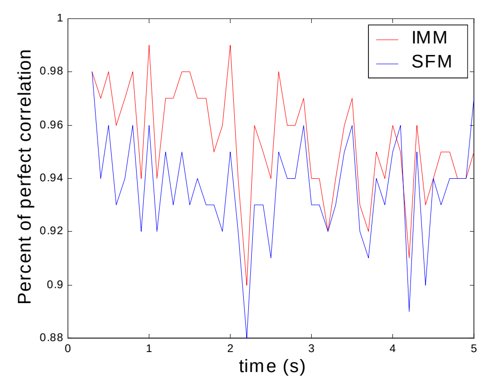

Fig3. the percent of perfect association

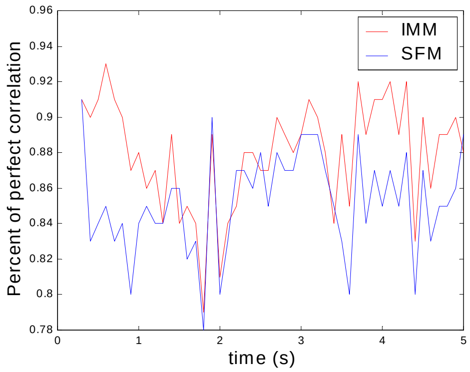

Fig4. the percent of perfect association

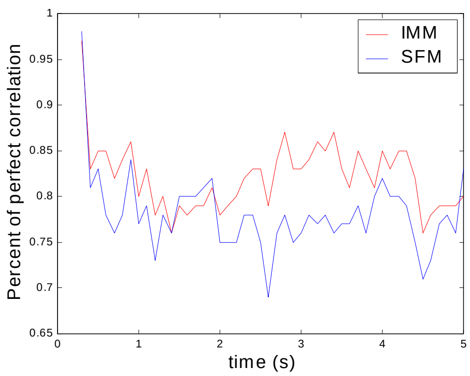

Fig5. the percent of perfect association

From the above results, we know that the proposed method can improve the tracking accuracy for multiple targets tracking in road situation, compared with the SFM method. The DS/IMM metho is effective and easy to realize in clutter environment.

7. Conclusion

The accurate tracking of multiple vehicles is a very important consideration in the design of active safety system. Data association and state estimate are the two important section of target tracking, in this paper, a data association method based on evidence theory and a state estimate method based on IMM algrothm are integrated into one algrothm for tracking the targets in road situation. The algrothm can avoid some problems encountered by other same kind of algorithms like NN and PDAF, and increase the tracking accuracy. Monte Carlo simulations have been provided to evaluate the performance of the method, and it is proved that the proposed method is simplicity, feasibility and efficiency.

References

[1] Sittler R W. An optimal data association problem in surveillance theory. IEEE Trans on Military Electronics.1964,8(2): 125-139.

[2] Blom H A P and Bar-Shalom Y. The interacting multiple model algorithm for systems with Markovian switching coefficients. IEEE Transactions on Automatic control, 1988, 33(8): 780-783.

[3] Gruyer D, Mangeas M., Alix R., «*Multi-sensor fusion approach for driver assistance systems*“, conf. IEEE ROMAN2001, 18-21 September 2001, Bordeaux.

[4] Rombaut M. Decision in multi-obstacle matching process using theory of belief. AVCS’98, Amiens: France, July 1-3,1998.

[5] Rombaut M, Berge-Cherfaoui V. Decision making in data fusion using Dempster-Shafer’s theory. 3th IFAC Symposium on Intelligent Components and Instrumentation for Control Applications, France, June 1997.

[6] Lin X., Kirubarajan T., Bar-Shalom T., Li X. Enhanced accuracy GPS navigation using the interacting multiple model estimator. Proc. 2000 Aerospace Conf. Big Sky, MT,2001.

[7] Lee M S, Kim Y H. New data association method for automotive radar tracking. IEE Proc.-Radar, Sonar, Navig. 2001, 148(5), 296-301.