

Application of Innovation Test in Cueing and Handoff with Intermittent Observations

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Abstract. The cueing and handoff between sensors with intermittent observation is deeply analyzed. This paper first analyzes the cueing and handoff demand and applies IMM-UKF algorithm to design the multi-sensor fusion tracking model. Then the innovation test and fuzzy functions are adopted to form the triggering criteria between the passive sensors and radar. Finally the simulation verifies the criteria and discusses the influence of detection probability in cueing and handoff.

1 Introduction

In the practical tracking processes, detection probability of multi-sensor systems is always less than one, due to shading of obstacles, fog, interference of weather conditions and so on. So that the detectability of each sensor is limited, and the measurement values are including many outliers. This is called the intermittent observation^[1]. As an important way of collaborative multi-sensor, cueing and handoff technique provide a better way of transferring the sensor that has large errors with high precision sensors to guide. Mainly reflected in the following two aspects: First, guide new selected sensors quickly capture the target; Second, ensure sustained visible target and fast relock by transferring tasks to other sensors, when the sensor is unable to complete the continuously detecting.

As for cueing and handoff, Wang Guo-hong[2] was the first to provide the successful cueing probability between infrared search and track system (IRST) and 3D radar. The papers [3][4] studied the equation and indicates between electronic support measures (ESM), IRST and radar in different places. In [5], the authors considered the handoff method in Multi-target Scenario, and proposed the optimal radar search schedule. These papers are based on probability theory and focuses on methods and performance of cueing and handoff. However, the goal of self-instruction process, intelligent enforcement mechanisms rarely involved.

In this paper, we focus on Cueing and Handoff between sensors with Intermittent Observations. First, analyze the demand of cueing and handoff. Then the multi-sensor fusion tracking sequential processing structure model with IMM-UKF algorithm was used and innovation test is applied to the sensor resource

scheduling. Finally the influence of detection probability in cueing and handoff between sensors is discussed.

2 Cueing and handoff demand in intermittent observations

Collaborative multi-sensor tracking system should adaptively optimize the allocation of resources based on the precision requirements and external environment, especially in intermittent observations[6]. When the outliers in the measured data have a bad effect on the precision, the cueing and handoff should be taken between the sensors. Here gives some rules of cueing and handoff:

- a) The result of cueing and handoff is to choose a sensor with good tracking performance and less resource consumption;
- b) Passive sensors should be prior to use, in order to reduce the electromagnetic radiation;
- c) The frequency of cueing and handoff should be limited;

To achieve the goal of executing cueing and handoff between phased array radar and passive sensors (ESM, IRST) spontaneously, this paper designs the quantified criteria to clear the triggering occasions, optimizes time resource allocation and spatial power distribution.

3 Radar, IRST, ESM interactive filter model

Consider the synergistic characteristics of sensors, a centralized fusion tracking model with sequential processing structure is used and we also apply the IMM-UKF algorithm into tracking.

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3.1 IMM-UKF algorithm

Figure 1 shows the IMM-UKF tracking algorithm, the algorithm uses target initial state and covariance as input, in turn determined by the recursive target state estimation and error covariance estimates next time [8].

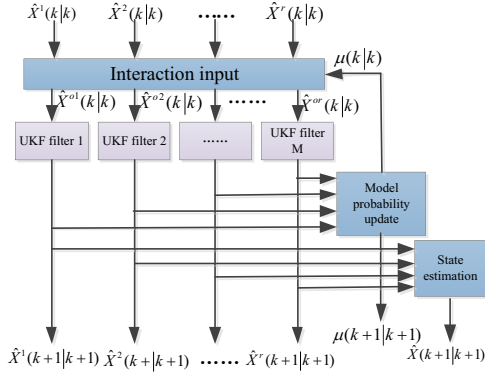


Fig 1 IMM-UKF Tracking Algorithm

We assume that the target initial moment of state is $\hat{X}(0|0)$ and covariance obtained $\hat{P}(0|0)$ from radar measurements, from the algorithm we could get the estimation of targets and its covariance:

$$\hat{X}_{k+1|k+1} = \sum_{i=1}^N \hat{X}_{k+1|k+1}^i \mu_{k+1}^i \quad (1)$$

$$P_{k+1|k+1} = \sum_{i=1}^N \mu_{k+1}^i [P_{k+1|k+1}^i + b \cdot b^T] \quad (2)$$

here, $b = [\hat{X}_{k+1|k+1}^i - \hat{X}_{k+1|k+1}]$.

3.2 Cueing and handoff based on innovation test

In intermittent observations, the statistically covariance is not optimal and could not identify the outliers [7]. While, innovation provide a suitable way to distinguish the outliers and also it can reflect the tracking accuracy.

In the IMM-UKF algorithm, each submodel i could generate innovation, which defines as: $V^i(k+1) = Z_{k+1} - \hat{Z}_{k+1|k}^i, i=1, \dots, M$, Z_{k+1} means the measurement in moment, and the prediction is $\hat{Z}_{k+1|k}^i$. The total innovation and its variance is:

$$V(k+1) = \sum_{i=1}^M \mu_{k+1}^i V^i(k+1) \quad (3)$$

$$S(k+1|k) = E[V(k+1) \cdot V(k+1)^T] \quad (4)$$

Here $S(k+1|k)$ is a multi-dimensional random variable, which is complex to deal directly and we apply the normalization processing and set $\xi_k = tr[S(k+1|k)]$ the trace of $S(k+1|k)$.

3.3. Innovation test in cueing and handoff

Considering the state equation and detecting equation of the target in k moment with intermittent observations:

$$X_{k+1} = A_k X_k + w_k \quad (5)$$

$$y_k = d_k C_k X_k + v_k \quad (6)$$

Here d_k is a bernoulli distribution, when $d_k = 1$ means the sensor get measurement normally; if there is no measurement: $d_k = 0$. v_k means measurement noise, its variance is R :

$$v_k \sim \begin{cases} N(0, R), d_k = 1; \\ N(0, \alpha^2 I), d_k = 0; \end{cases} \quad (7)$$

According to the theoretical target tracking, if $d_k = 1$, the measurement is useful and the sensor can keep detecting the target; when $d_k = 0$, the sensor gets nothing but outlier. Here we define the detection probability of $d_k = 1$ is λ .

Innovation can reflect the tracking quality of the sensor and the value of d_k . Therefore, we design the trigger criterions of cueing and handoff based on the innovation test, two thresholds $r_1, r_2 (r_1 > r_2)$ was set to predicate the value of d_k :

a) If $\xi_k < r_2$, we assume that $d_k = 1$.

b) If $\xi_k > r_1$, we assume that $d_k = 0$.

c) If $r_2 < \xi_k < r_1$, we could not sure the value of d_k , directly. The confidence of ξ_k is fuzzed by means of fuzzy membership function:

$$\mu(\xi_k) = \begin{cases} 1, & \xi_k < r_2 \\ -\frac{\xi_k - r_1}{r_1 - r_2}, & r_2 < \xi_k < r_1 \\ 0, & \xi_k > r_1 \end{cases} \quad (8)$$

To determine the trigger timing of cueing and handoff is to choose the proper time, and two steps are needed: confirm the value of d_k every moment and then take T as period, here $T = N\Delta t$, if in this period the innovation test shows that d_k is sustainably equal to 0, then it will trigger the cueing and handoff.

Fig 5 shows the trigger criterions of cueing and handoff. Here the estimated covariance error is predicted by the filtering algorithm. When the state estimation error exceeds the preset limit, we consider that targets need to be cued and handoff.

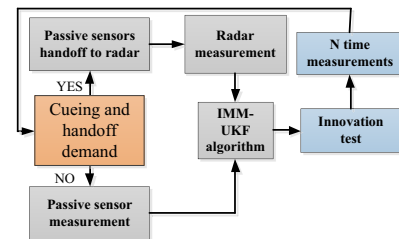


Fig 2 Trigger criterions of cueing and handoff

4 Simulation and analysis of trigger criterions

4.1 simulation environment settings

In this section, we established motion trail of a target, make sure its initial position and velocity. Assume the

angle mean square error of radar, ESM, IRST is 0.2° , 0.5° and 0.1° respectively, and the distance mean square error of radar is $100m$.

4.2 model parameter settings

The simulation is based IMM-UKF sequential filtering algorithm for target tracking, and the maneuvering model chooses a CV model, CT model and a CS model, the initial probability of each model are:

$$\pi_0 = \left[\frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right]$$

Transition probability between the models:

$$\pi_{ij} = \begin{bmatrix} 0.9 & 0.05 & 0.05 \\ 0.05 & 0.9 & 0.05 \\ 0.05 & 0.05 & 0.9 \end{bmatrix}$$

Model system error:

$$Q_{CV} = Q_{CT} = Q_{CS} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Radar, the measurement errors are as follows:

$$R_k^1 = \begin{bmatrix} 100^2 & 0 & 0 \\ 0 & 0.2^2 & 0 \\ 0 & 0 & 0.2^2 \end{bmatrix}, \quad R_k^2 = \begin{bmatrix} 0.3^2 & 0 \\ 0 & 0.3^2 \end{bmatrix},$$

$$R_k^3 = \begin{bmatrix} 0.1^2 & 0 \\ 0 & 0.1^2 \end{bmatrix}$$

4.3 Results and Analysis

In this section, we address the Simulation in three cases respectively, and discuss "the number of passive sensors' measurements" and "the detection probability λ " that are associated to the trigger timing.

Case 1: Assume that the detection probability of ESM is $\lambda_E = 0.6$, IRST is $\lambda_I = 0.7$ and radar is $\lambda_R = 0.7$. The sequence measurement of the sensors is shown in Fig 3, the track is shown in Fig4.

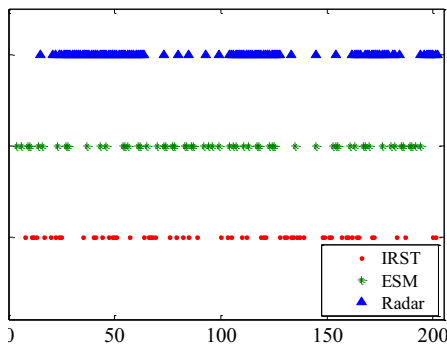


Fig 3 Sequence measurement of the sensors

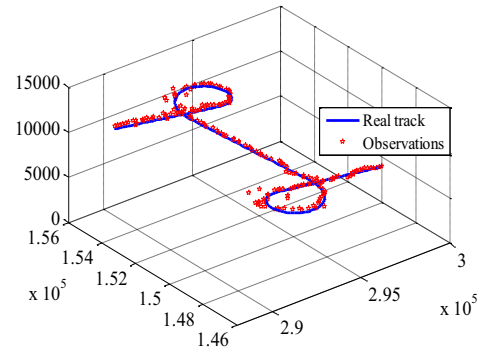


Fig 4 Tracking trajectory

The cueing and handoff between passive sensors and radar is triggered in 15th bat. The tracking task continues to execute by passive sensors.

Case 2: Assume that the detection probability of ESM is $\lambda_E = 0.8$, IRST is $\lambda_I = 0.8$ and radar is $\lambda_R = 0.7$. the track is shown in Figure 5.

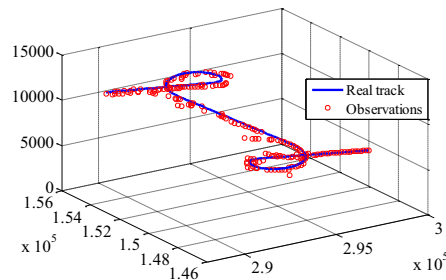


Fig 5 Tracking trajectory

Compared to the case 1, we know that the increasing λ_E or λ_I means a higher tracking accuracy. Passive sensors can get more measurements and the number of cueing and handoff between passive sensors to radar decreases, thereby reducing the need of radar resources.

Case 3: Assume that the detection probability of ESM is $\lambda_E = 0.6$, IRST is $\lambda_I = 0.7$ and radar is $\lambda_R = 0.4$. the track is shown in Figure 6.

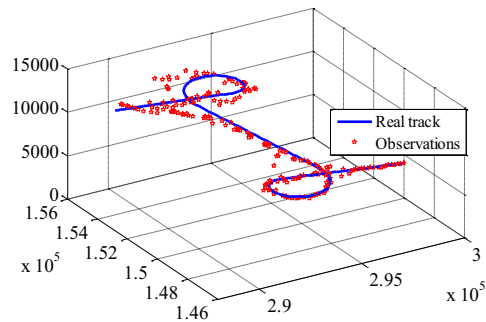


Fig 6 Tracking trajectory

In summary, the trigger criterions based on innovation test is effective, the detection probability λ can influence the number of measurements and the trigger timing of cueing and handoff. In the practical application, the rate of cueing and handoff should not be frequent, so we also should consider the thresholds in the innovation test.

5 Conclusion

In this paper, we have discussed the cueing and handoff between passive sensors and radar with intermittent observations and designed trigger criterions of cueing and handoff that can determine the needs and the best time to execute spontaneously. Firstly, the cueing and handoff between passive sensors and radar in sensors cooperative tracking have been deeply analyzed, followed by the IMM-UKF algorithm and innovation test has been introduced to solve the tracking resource scheduling. Finally, the trigger criterions were verified and the factors of cueing and handoff were discussed.

Observations[C]//Proof the 47th IEEE Conference on Decision and Control,2008. 2692-2697

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References

1. Chen Li, Xu Zhi-gang, SHENGAn-dong. Filter design for a class of nonlinear optic-electric tracking system with intermittent observation[J]. *Acts Aeronautics et Astronautics Sinics*,2009,30(9):1745-1753.
2. Wang Guo-hong, He You and Mao Shi-yi. Performance analysis of using an IRST sensor cueing a 3D radar[J]. *Journal of Electronics*, 2002 (12): 1738-1740.
3. Peng Rui-Hui, Wang Shu-zong, Lu Yong-sheng and Wang Xiang-wei. Analysis of ESM cueing 2D radar located at different sites[J]. *Modern radar*, 2009, 31 (1): 13-16.
4. Lv Yong-sheng, Wang Shu-zong. Analysis of IRST cueing to 3D radar at different sites[J]. *Infrared and Laser Engineering*, 2008, 37 (5): 911-915.
5. Zhang Hua-rui, Yang Hong-wen and Yu Wen-xian. The handoff method of IRST and radar under multi-target scenario[J]. *Electronics & Information Technology*, 2011, 33 (5): 1101-1106.
6. Chen Li, Wang zhong-xu, and Wang Bo. Optic-Electric tracking system filter design based on posterior confidence residual test with intermittent observations [J].*ACTA ELECTRONICA SINICA*, 2012,40(5):941-948.
7. Chen Li, Wang zhong-xu. Research on Data Mining of Redundant Angle Information in Optic-electric Tracking System with Intermittent Observations[J]. *ACTA ARMAMENTARII*, 2011,32(7) :819-826.
8. Kang Yu, Xiao Xiao-bo. An interacting multiple algorithm incorporating maneuver detection for target tracking[J]. *Modern Radar*, 2004, 26(12):33-36.
9. Lu Di, Yao Yu, He Feng-hua. Kalman filter restraining outliers[J]. *Journal of System Simulation*, 2004, 16(5):1027-1029.
10. [10] Sinopoli B, Mo Y. A Characterization of the Critical Value for Kalman Filtering with Intermittent