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Dynamic Sensor Management Algorithm Based on Improved Efficacy Function

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Abstract: A dynamic sensor management algorithm based on improved efficacy function is proposed to solve the multi-target and multi-sensory management problem. The tracking task precision requirements (TPR), target priority and sensor use cost were considered to establish the efficacy function by weighted sum the normalized value of the three factors. The dynamic sensor management algorithm was accomplished through control the diversities of the desired covariance matrix (DCM) and the filtering covariance matrix (FCM). The DCM was preassigned in terms of TPR and the FCM was obtained by the centralized sequential Kalman filtering algorithm. The simulation results prove that the proposed method could meet the requirements of desired tracking precision and adjust sensor selection according to target priority and cost of sensor source usage. This makes sensor management scheme more reasonable and effective. *Copyright © 2016 IFSA Publishing, S. L.*

Keywords: Efficacy function, Sensor management, Kalman Filter, Error covariance.

1. Introduction

More requirements are requested about the environment sensory ability of the airborne information platform (AIP) under the diversified target, complex environments and multiple tasks situation. Many (kinds of) sensors are disposed to this kind of platform, so we can give full play on sensor coordinated work and sensor management technology. Faced with multiple targets and tasks, the limited sensor source has a core problem which is to optimize the distribution and allocation.

Document [1-2] set phased array radar as a study object for tracking task, the methodology for beam scheduling in multi-target tracking was proposed. Document [3-5] solved the target tracking task in centralized multisensory systems based on the method of covariance control. These methods above concentrated on high tracking precision, lacking of effective control to task tracking. Document [6-8] was based on the needs of tasks requirement, established an allocation model according to the tasks requirement and brought out dynamic sensor source allocation algorithm. Document [9-10] established a sensor allocation plan which was independent from the tracking cycle system, and was an off-line predictive allocation substantially. Document [11-13] overcame the sensor management problem during tactical monitoring action, taking out studies mainly on task distribution, sensor-source pairing and some other aspects.

Concentrating on the AIP sensor and task feature, the tracking task precision requirements (TPR), target priority, sensor use cost and some other factors are considered comprehensively to establish an efficacy function. From the viewpoint of controlling covariance, normalized distance function and normalized filtering covariance are weighted to assign the pairing coefficient and dynamically confirm the result of "target-sensor (combination)". Under the multi-target tracking situation, simulation proves the efficiency of the sensor management method.

2. Sensor Management Model

Under the practical multiple tracking situation, the target tracking of sensor system only reflects on the tracking precision. Firstly, there is no need to maintain a high precision tracking on the low priority target. Secondly, due to the restriction from the sensory ability of sensor, it will cost differently while using different sensor. While improving sensory ability of one certain target, it surely has side effect on the other target tracking and task searching. Thirdly, using the active radar to maintain the targets measurement may bring vital threat to self-surviving.

Assuming that m sensors track n targets at the same time, there are $m'=2^m-1$ kinds of sensor combinations which certain $m'-m$ fake sensors. Hence, considering the precision need for target tracking task, target priority and the cost of sensor use, we describe the allocation as follows,

$$E^{opt} = \arg\max\left(\sum_{i=1}^{m'}\sum_{j=1}^{n} ef_{ij}(pa_{ij}(\cdot), pr_j, c_i)\cdot x_{ij}\right)$$
$$st. \quad \sum_{j=1}^{n} x_{ij} \le S_i, i = 1,2,......,m' \qquad (1)$$
$$\sum_{i=1}^{m} x_{ij} = 1, j = 1,2,3,......,n$$

where E is the efficient value corresponding with the sensor optimal allocation strategy. x is the allocation case of sensors, x_{ij} means distribute sensor i to target j, conversely x_{ij} =0 means no distributing; in the equation, pa_{ij} is the pairing function when sensor i and target j, which is related with the target task accomplishment condition. pr_j is the priority function for target j, c_i is the cost of sensor use. ef_{ij} is the efficacy of sensor i which allocation to target j, the better the accomplishment condition is, the higher the priority is, the smaller the cost of sensor use is, the bigger the value of ef_{ij} will be.

Allocation restriction includes the maximum restriction of tracking ability (the tracking task allocation to each sensor can not be more than the limited capacity) and restriction of target cover (each one target should be allocation to one sensor at least).

3. The Establishment of Efficacy Function

3.1. Sensor-target Pairing Function

The pairing function *paij* when target j allocates to sensor i is related to the TPR. Since the precision of tracking period and collimation period are different, the expected TPR is different as well, even if considering one target. We can describe the tracking precision need through the differences between practical evaluating covariance matrix (PECM) and desired covariance matrix (DCM). We can use determinant of matrix, trace of matrix, or matrix metrics derived from different matrix norms. Different result coming from different method may bring different effect on TPR [8-9], we choose trace of matrix to measure the differences between expecting covariance P_d and practical covariance, that is to say,

$$f_P = f(P, P_d) = -tr\left[P_d - P\right] \qquad (2)$$

Since the covariance matrix is not negative, we assume that A, $B \in R^{n\times n}$, $A=A^T\ge 0$ and $B=B^T\ge 0$. Define the difference between two matrixes is $M=A-B$, so, $M=M^T$, distance function f(A,B) can be expressed as,

$$f(A,B) = tr(|m|) = \sum_{i=1}^{n}|m_{ii}| \qquad (3)$$

target-sensor (combination) pairing function $pa(x_1, x_2, ...; y_1, y_2, ...)$ should obey the equations Max $pa(\ )=1$, and Min $pa(\ )=0$, so TPR can not be used in this model directly. Evaluated $pa_{ij}(\ )$ with the weighted sum of the normalized distance function $1-\Delta f(P,P_d)$ and normalized filtering error covariance norm $\Delta\rho$. The pairing function was defined as:

$$pa_{ij} = \alpha\times[1-\Delta f(P,P_d)] + \beta\times\Delta\rho \qquad (4)$$

where $\Delta\rho=\|\Delta P\|$, weight coefficient α, β reflect the effect on pairing function from filter covariance and different measure method between two matrices. Herein, $\alpha+\beta=1$ ($\alpha>0, \beta>0$) [8].

3.2. Target Priority

Many factors affect target priority, but we usually take the following factors into consideration: target identification (*ID*), information requirement (*IM*), target threat (*FR*), attack chance (*CH*), fire-control requirement external commands (*EC*), etc., so we can define a priority function *pr*(*ID, IM, TR, CH, FR*) whose value can be calculated with these five factors. According to the practical experience, we can figure out the concrete form of the function. No matter what the form of function is, we confirm the priority on the basis of the following requests:

1) Put the locked target on the very first position;
2) Then the target we can attack;
3) Next the enemy target and undefined state follows;
4) Finally friend and ourselves;
5) The external commands owns the highest priority, assuming $pr(\ )=1$.

The simplest and most practical expression is the linear sum of the five factors multiply its own coefficient

$$
\begin{aligned}
& pr(ID, IM, TR, CH, FR) \\
& = \chi \times ID + \delta \times IM + \gamma \times TR + \varepsilon \times CH + \eta \times FR
\end{aligned} \tag{5}
$$

The higher the priority for the target is, the smaller the value of $pr(\ )$ is to meet the principle that the higher priority is, the bigger the value of ef_{ij}, and the value is smaller than 1, we take reciprocal value for priority function, that is to say, as to the target j, the priority degree is $\overline{pr}_j = 1 / pr_j$.

3.3. Sensor use Cost

Based on different practical situation, the definition of "sensor use cost" can be explained differently. As to different kinds of sensor allocated to AIP, when use active sensor to measure target constantly, it may bring threat to self-surviving. However, the passive sensors are in the passive state all the time, and will never be exposed. From this degree, the "use cost" of active radar is much bigger than passive radar and it is the same to active sensor (such as phased array radar), the use cost for different performance is not the same. Normally, the Radars improve their detecting precision by increasing the data updating rate, so improving the precision in certain domain of space will consume more time as "use cost". The higher the detecting precision of sensor is, the larger the use cost is. We usually confirm the cost according to the sensor number, sensor type, sensor performance and some other factors in a comprehensive way.

The bigger the sensor use cost is, the bigger the value of c_i is. To meet the principle that the value of ef_{ij} increases as the use cost increases and the value of use cost is smaller than 1, we take negative normalized value for sensor use cost function, that is to say, as to the sensor i, the sensor use cost is $\overline{c}_i = -c_i \Big/ \sum_{i=1}^{n} c_i$.

In conclusion, we establish efficacy function as

$$
ef_{ij}(pa_{ij}, pr_j, c_i) = \omega \times pa_{ij} + \xi \times \overline{pr}_j + \lambda \overline{c}_i \tag{6}
$$

Herein, coefficient ω, ξ, λ reflect the effect on efficacy from pairing, priority and cost. The basic principle is that the priority has much greater effect on efficacy than what pairing coefficient does, and the pairing coefficient has much greater effect than what sensor use cost does.

4. "Sensor – target" Allocation Algorithms

When given DCM $\boldsymbol{P}_d$ of the target, we can iterate the Kalman filtering equation to figure out the filtering error covariance, and then find the allocation efficacy. When couples of sensors are allocated to one target, covariance matrix for each sensor to measure targets are different, so we import a centralized sensor Kalman sequential algorithms to solve the target measuring problem with sensor combination.

4.1. Covariance Matrix Algorithms

Assuming target discretizing state equation expressed as

$$
x(t_{k+1}) = F(T_k)x(t_k) + G(T_k)w(t_k) \tag{7}
$$

Herein, $x(t_k)$ is the state vector to time t_k, $w(t_k)$ is the system noise vector, and its covariance matrix is $Q(t_k)$. $F(T_k)$ is the transforming matrix to time t_k, $G(T_k)$ is the input matrix to time t_k. $T_k = t_{k+1} - t_k$ is the sample interval to time t_k.

The measuring equation for sensor is as follow:

$$
z_j(t_k) = H_j x(t_k) + v_j(t_k), j = 1, 2, \ldots\ldots, m' \tag{8}
$$

Herein, $Z_j(t_k)$ is the measure vector of sensor j to timet_k, $v_j(t_k)$ is measure noise, and its covariance matrix is $R_j(t_k)$, H_j is observation matrix.

As to arbitrarily pseudo sensor D_i from the pseudo sensor set D, the centralized sensor Kalman sequential algorithms is as follow,

$$
(x(t_k))^1 = x(t_k^-) + (K(t_k))^1 (z_1(t_k) - H_1 x(t_k^-)), \tag{9}
$$

$$
\begin{aligned}
(x(t_k))^K = {} & (x(t_k))^{K-1} + (K(t_k))^K \cdot \\
& (z_K(t_k) - H_K x(t_k))^{K-1},
\end{aligned} \tag{10}
$$

$$
x(t_k) = (x(t_k))^{N_i}, K \in D_i \tag{11}
$$

Herein the sequential gain can expressed as

$$
(K(t_k))^1 = P(t_k^-) H_1^T (R_1(t_k) + H_1 P(t_k^-) H_1^T)^{-1}, \tag{12}
$$

$$
\begin{aligned}
(K(t_k))^K = {} & (P(t_k))^{K-1} (H_K^T (R_K(t_k) \\
& + H_K (P(t_k))^{K-1} H_K^T)^{-1},
\end{aligned} \tag{13}
$$

filtering covariance matrixes (FCM)$P(t_k)$ are

$$
(P(t_k))^1 = (I_n - (K(t_k))^1 H_1) P(t_k^-), \tag{14}
$$

$$
(P(t_k))^K = (I_n - (K(t_k))^K H_K) P(t_k)^{K-1}, \tag{15}
$$

$$
P(t_k) = (P(t_k))^{N_i}, K \in D_i \tag{16}
$$

Predictive value $x(t_k^-)$ and predictive error covariance matrix $P(t_k^-)$ are respectively

$$
x(t_k^-) = F(T_{k-1}) x(t_{k-1}), \tag{17}
$$

$$P(t_k^-) = F(T_{k-1})P(t_{k-1})F^T(T_{k-1}) + G(T_{k-1})Q(t_{k-1})G^T(T_{k-1}) \quad (18)$$

Herein, $(\bullet)^K$ means disposed by K sensors.

Distance function of FCM and DCM is changed by Dynamic state value of filtering time. During the Dynamic control procedure we can treat the FCM as PECM, and the TPR f_P is

$$f_p(\boldsymbol{P}(t_k), \boldsymbol{P}_d) = tr\left[\boldsymbol{P}(t_k) - \boldsymbol{P}_d\right] \quad (19)$$

4.2. Allocation Algorithms Steps

Based on the analysis above, we can bring the steps of "sensor – target" allocation algorithms into conclusion:

Step 1. Initialize the number of sensor i=1;

Step 2. Calculate the predictive error covariance $\boldsymbol{P}(t_k^-)$ matrix at t_k^- according to (18);

Step 3. Calculate the FCM $\boldsymbol{P}(t_k)$ at t_k after the D_i sensor measurement according to (13);

Step 4. Measure the distance between FCM and DCM at t_k according to (19);

Step 5. Calculate the pairing coefficient $pa_{ij}(\ )$ according to (4);

Step 6. Calculate allocation ef_{ij} according to (6);

Step 7. Loop the steps above, and then complete the dynamic allocation based on (1).

5. Simulation Analysis

Considering 3 sensors track 4 targets at the same time, and the coordinate for each target is (x,y). Assuming that the simulation cycle is 1 s, and the simulation time is 100 s. Herein, the tracking precision of sensor S1 at x axis direction is relatively higher. The tracking precision of sensor S2 at y axis direction is relatively higher, the tracking precision of sensor S3 at both x and y axis direction are relatively low. Tracking capacity is the total number a sensor can track at the same time, the correlation coefficient reflects the correlate degree of noise between two axes.

There were 2^3-1=7, seven sensor combinations should be considered coming from the randomly combination between sensors. In simulation of this paper, the coefficient in Formula (6) is ω=0.21, ξ=0.46, λ=0.33.

The particular set of measure noise parameter for the sensors and their tracking capacity was listed in Table 1.

The normalized sensors use cost was listed in Table 2.

We take filtering covariance (FC), ID, Target lock-on, Weapon state, type information (TI) and some other factors into consideration when measure the target priority. We can check the current value of priority quantification in Table 3. The factors coefficient in the simulation is supposed to the same, the sequence of target priority can be calculated. The tiptop priority is target 2 and the lowest priority is target 4, the relationship is $\overline{pr}_2 > \overline{pr}_1 > \overline{pr}_3 > \overline{pr}_4$.

Table 1. Measuring noise analysis of each sensor (standard deviation: meter).

Sensor	x axis direction standard deviation	y axis direction standard deviation	Correlation coefficient	Tracking capacity
Sensor 1	9.23	20.9	-0.61	2
Sensor 2	22.1	8.2	0.82	3
Sensor 3	41.4	43.7	-0.94	4

Table 2. Sensor (combination) normalized use cost.

Sensor number	Normalized use cost ($\overline{c}_i$)
S1 (Sensor1)	-0.05
S2 (Sensor2)	-0.075
S3 (Sensor3)	-0.125
S4 (Sensor1+ Sensor2)	-0.125
S5 (Sensor1+ Sensor3)	-0.175
S6 (Sensor2+ Sensor3)	-0.2
S7 (Sensor1+ Sensor2+ Sensor3)	-0.25

Table 3. Current quantification of target priority.

	FC	ID	Target lock-on	Weapon state	TI
Target 1	0.45	1	0	0	0.853
Target 2	0.50	0	0	0	0.106
Target 3	0.60	1	0	0	0.734
Target 4	0.80	1	0	0	0.808

Suppose the DCM in 1~50 s as Pd_1=Pd_2=Pd_3=Pd_4=$diag$(30, 1, 30, 1), set the DCM in 51~100 s as

Target 1: *Pd1=diag(10, 0.3, 30, 1)*;

Target 2: Pd_2=$diag$(30, 1, 1 0, 0.3);

Target 3: Pd_3=$diag$(30, 1, 30, 1);

Target 4: Pd_4=$diag$(10, 0.3, 10, 0.3).

The maneuvering noise covariance matrixes of these four targets are listed as follows:

$$Q_1 = \begin{bmatrix} 0.35 & 0 \\ 0 & 0.45 \end{bmatrix},\ Q_2 = \begin{bmatrix} 0.12 & 0 \\ 0 & 0.20 \end{bmatrix},$$
$$Q_3 = \begin{bmatrix} 0.20 & 0 \\ 0 & 0.15 \end{bmatrix},\ Q_4 = \begin{bmatrix} 0.70 & 0 \\ 0 & 0.85 \end{bmatrix}$$

The filtering covariance for targets are given in Fig. 1.

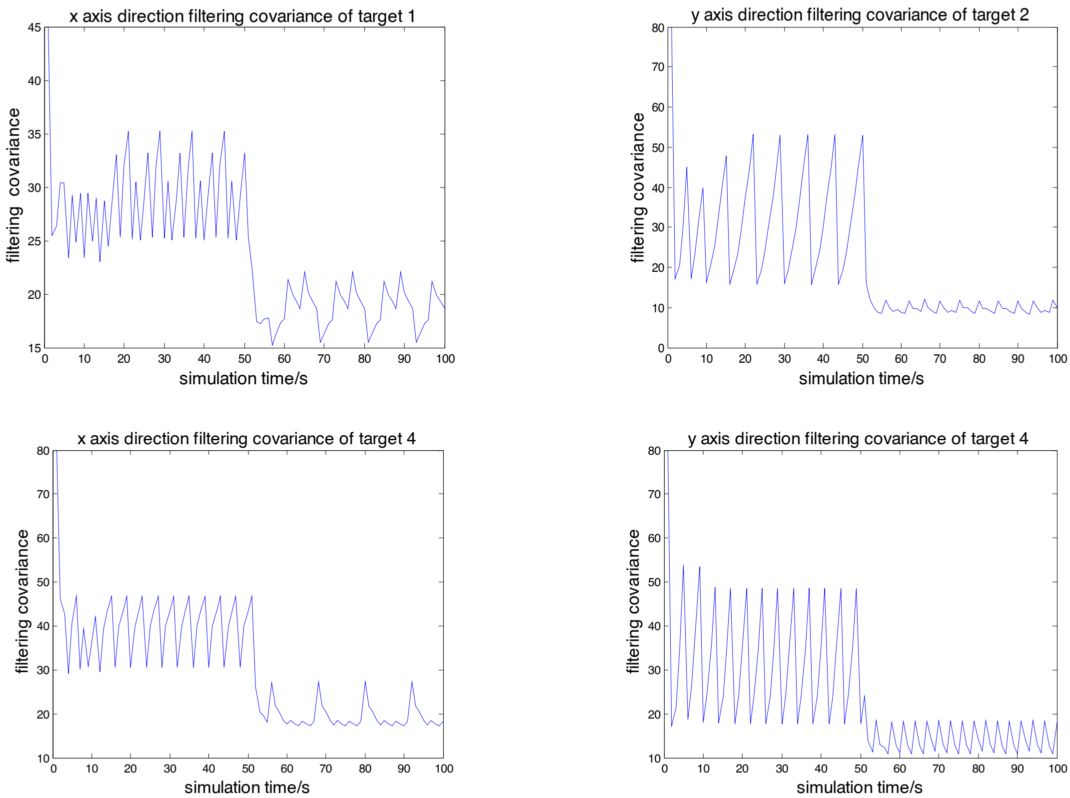

Fig. 1. Covariance control effect.

From simulation chart 1, we can see, due to improvement of the precision, the filtering covariance of each target can convergence to expectation degree, and can basically reach the requirement of adaptive covariance control. Since we import a target priority function in allocation efficacy, the source the highest target 2 get can perfectly reach the requirement of target tracking. From chart 3 we can see that, the tracking performance of target 2 is better than target 1.

The Pairing result of ‘Target-Sensor’ is shown in Fig. 2.

During 51~100 s, the tracking precision of x axis improves and the sensor S1 was allocated to target 1 increasingly. However the priority of target 1 is relatively low, and the tracking capacity of S1 is the weakest, so the target 1 can not sostenu to occupy the source of S1, and the result of source allocation is changeable all the time. When the tracking precision of target 2 on y axis improves, sensor combination S6 (includs S2) was allocated to the target increasingly. Due to the highest priority of target 2, it can occupy the source of S6 in the most time to meet the requirement of precision on y axis. For the tracking precision of target 3 is constant in the latter 50 s, the result of sensor source allocation acts steadily and the target gets the least sensor source. The expected covariance of target 4 on x axis and y axis were decreased, so the improvement of tracking precision leads sensor combination S4 (includes S1 and S2) was allocated to the target increasingly.

As for the influence of sensor use cost factor, the pairing result of ‘Target-Sensor’ without cost is simulated, the result was shown in Fig. 3.

Comparing to the Fig. 2, it can be clearly seen in the Fig. 3 that pairing result of ‘Target-Sensor’ without cost of each target, the high cost sensor (sensor combination) were more allocated.

From the simulation above we can see that the algorithm we give in this paper could dynamically allocate the sensor source reasonably based on covariance matrix, target priority, and sensor use cost.

6. Conclusions

A dynamic sensor management algorithm based on improved efficacy function is proposed to overcome the sensor management difficulties during face to multi-tasks on AIP. This paper brings about the assignment of sensor to pairing coefficient and auto update. Meanwhile we introduce target priority function and sensor use cost to the efficacy function and give an adaptive allocation algorithm based on the linear programming. Furthermore we conduct the algorithm simulation. The result of simulation shows that this algorithm combines the advantages of covariance adaptive control and target weight. So this algorithm could adaptively allocate the sensor source based on expectation of tracking precision and dynamically adjust the sensor source according to the target priority degree and the sensor use cost. In summarize, this algorithm improves the rationality and effectiveness for sensor source allocation.

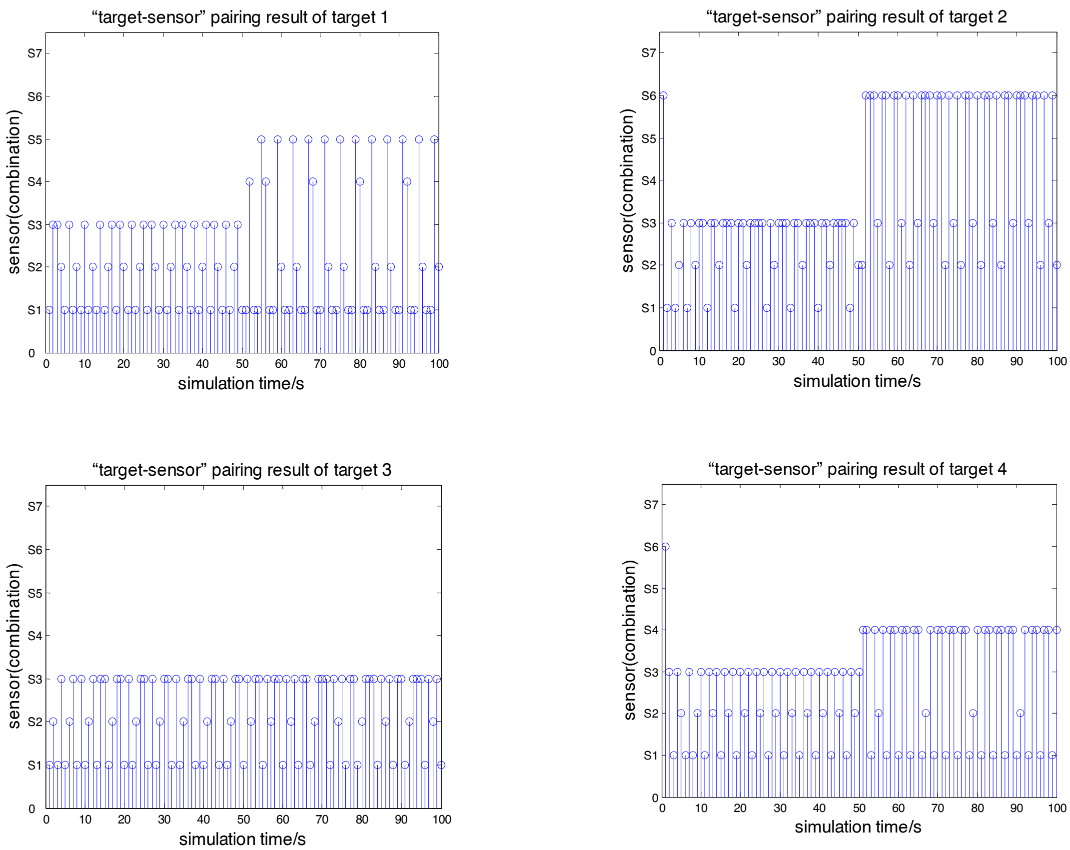

Fig. 2. Pairing result of 'Target-Sensor'.

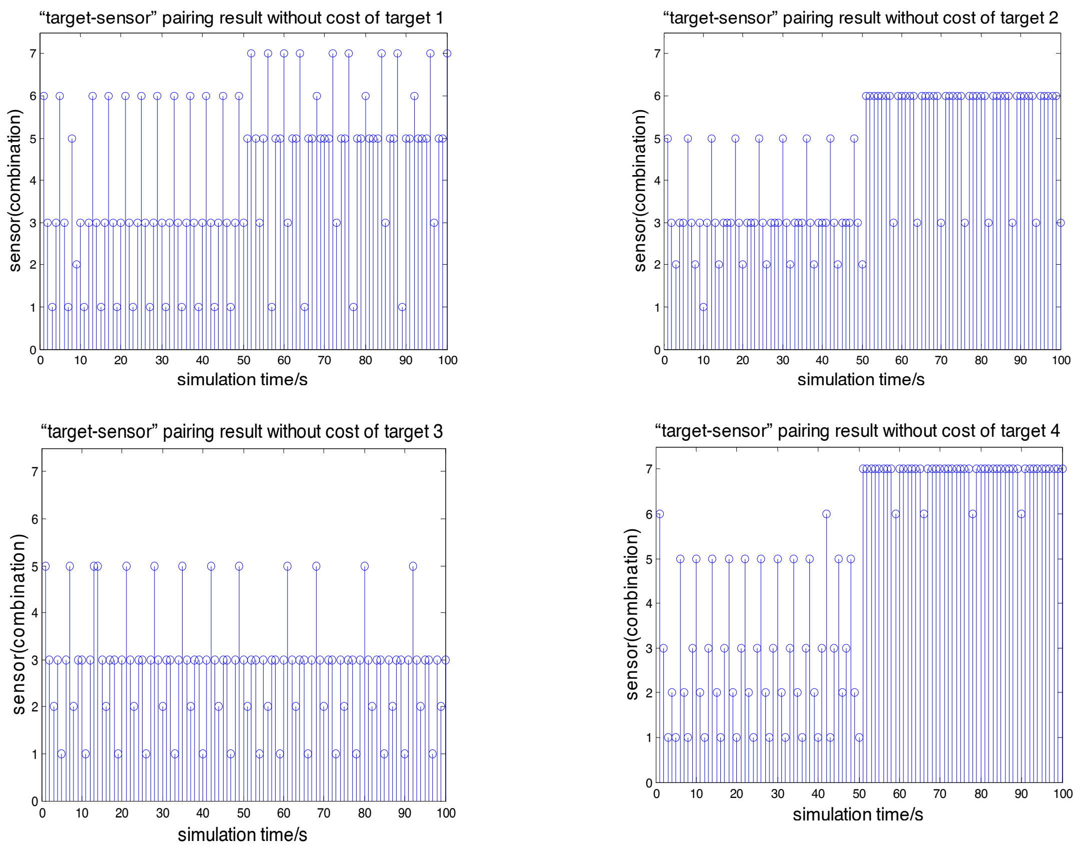

Fig. 3. Pairing result of 'Target-Sensor' without cost.

References

[1]. Krishnamurthy V., Evans R. J., Hidden Markov model multi-arm bandits: a method ology for beam scheduling in multi-target tracking, *IEEE Transactions on Signal Processing*, Vol. 49, No. 12, 2001, pp. 2893-2908.

[2]. V. Krishnamurthy, D. V. Djonin, Optimal threshold policies for multivariate POMDPs in radar resource management, *IEEE Transactions on Signal Processing*, Vol. 57, No. 10, 2009, pp. 3954-3969.

[3]. M. Kalandros, Pao L. Y., Covariance control for multisensory systems, *IEEE Trans. on Aerospace and Electronic Systems*, Vol. 38, No. 4, 2002, pp. 1138-1157.

[4]. M. Kalandros, Pao L. Y., Multisensor Covariance Control Strategies for Reducing Bias Effects in Interacting Target Scenarios, *Trans. on Aerospace and Electronic Systems*, Vol. 41, No. 1, 2005, pp. 153-173.

[5]. Lu J. B., Hu W. D., Xiao H., *et al.*, Novel cued search strategy based on information gain for phased array radar, *Journal of Systems Engineering and Electronics*, Vol. 19, Issue 2, 2008, pp. 292-297.

[6]. Cui B. X., Xu Y. S., Xia H. B., *et al.*, Dynamic multi-sensor management algorithm based on task control, *Journal of Systems Engineering and Electronics*, Vol. 34, No. 12, 2012, pp. 2473-2478.

[7]. Wang L., Yu L., Kou Y. X., *et al.*, Multi-sensor resource management method drive by task requirement, *Journal of Systems Engineering and Electronics*, Vol. 32, No. 9, 2010, pp. 1925-1930.

[8]. Kreucher C. M., Hero A. O., Kastella K. D., A comparison of task driven and information driven sensor management for target tracking, in *Proceedings of the IEEE Conference on Decision and Control and the European Control Conference,* 2005, pp. 4004-4009.

[9]. Boers Y., Driessen H., Nederland T., Results on the modified Riccati equation: Target tracking application, *IEEE Trans on Aerospace and Electronic Systems*, Vol. 42, No. 1, 2006, pp. 379-384.

[10]. Tong J., Shan G. L., Study of multi-sensor allocation based on modified Riccati equation and Kuhn-Munkres algorithm, *Control and Decision*, Vol. 27, No. 5, 2012, pp. 747-751.

[11]. C. J. Cohen, F. Morelli, K. A. Scott, A surveillance system for the recognition of intent within individuals and crowds, in *Proceedings of the IEEE Conference on Technologies for Homeland Security*, May 2008, pp. 559-565.

[12]. A. Benaskeur, H. Irandoust, Sensor management for tactical surveillance operations, *Aerospace Science and Technology*, Canada, Vol. 11, 2007, pp. 327-338.

[13]. Liu B., Zhao Y., Yi D. Y., Sensor Management based on Covariance Control Strategy for LEO Satellite Constellation, in *Proceedings of the 4th International Symposium on Computational Intelligence and Design*, Vol. 1, Oct. 2011, pp. 282-285.