Research Journal of Applied Sciences, Engineering and Technology 7(7): 1432-1437, 2014
DOI:10.19026/rjaset.7.413
ISSN: 2040-7459; e-ISSN: 2040-7467
© 2014 Maxwell Scientific Publication Corp.
Submitted: May 16, 2013 Accepted: June 11, 2013 Published: February 20, 2014

Research Article

An Improved Optimal Measurement Data Correlation Algorithm Based on Multi-Source Information

[1]Zhaofeng Su, [2]Yifan Wang, [1]Yuanyuan Duan and [1]Li Zhou
[1]School of Information and Electrical Engineering, Ludong University, Yantai 264025, China
[2]Business School, University of Shanghai for Science and Technology, Shanghai 200093, China

Abstract: An improved optimal 3-Dimensional (3-D) assignment algorithm based on Multi-source Information (IMFOA) is proposed. The algorithm firstly gets the correlation degree between multi-source measurements of single-sensor and target track through fusing multi-source information by using grey relational analysis algorithm and then a 3-D assignment model based on multi-source information fusion can be got. Further, an improved point-track optimal assignment algorithm is used to complete point-track correlations. In comparison with the Optimal 3-D Assignment (OA) algorithm based on dynamic information and the Improved Optimal Assignment (IOA) algorithm which implements point-track correlation through using marginal correlation probability on the basis of OA algorithm, IMFOA algorithm improves the tracking accuracy of multi-target in varying degrees under different detection scenarios and is an optimal measurement data correlation algorithm with stronger anti-interference.

Keywords: Data correlation, grey relational analysis algorithm, multi-source information

INTRODUCTION

In general, algorithms of multi-target tracking merely use state measurement information of target for multi-target location and tracking, leading to poor anti-interference performance. Especially in dense target and clutter environment, the uncertainty of sources of state measurement increases and this leads to wrong and leakage of correlations, resulting in worse multi-target tracking effect (Han *et al*., 2010; Pan *et al*., 2009). With the progress of science and electronic technology, especially the sensor detection technology and computer information processing technology, sensors can acquire a lot of other feature information besides state measurement. For example, the carrier frequency of the Radiation Source (RF), Pulse Repetition Interval (PRI), Pulse Width (PW) and so on. These features reflect the inherent attribute information of target, if multi-source information including state and different feature information can be effectively fused, it will help to decrease the uncertainty of state measurement and improve the accuracy of multi-target tracking and location (Wang *et al*., 2006; Wang and Luo, 2004).

Data correlation is the core issue of multi-target tracking. Joint Probabilistic Data Association (JPDA) algorithm and Generalized Probabilistic Data Association (GPDA) algorithm are two kinds of suboptimal data correlation algorithms which are the most commonly used in the practical application. Studies have shown that whether in dense or general target detection environments, the performance of GPDA algorithm is superior to JPDA algorithm (Pan *et al*., 2005). However, the structure of information processing of serial multi-sensor GPDA algorithm is cascade, in the sequential processing on the measurement data from different sensors, measurement errors and data processing errors of each of the sensors are gradually magnified and accumulated, affecting the performance of multi-target tracking (Zhang *et al*., 2007; Xu *et al*., 2005). And the calculation burden of the traditional optimal assignment algorithm on the basis of likelihood ratio of measurement data division is too heavy. In view of the above condition, on the basis of the optimal 3-D assignment algorithm based on dynamic information, an improved optimal 3-D assignment algorithm on the basis of multi-source information fusion is proposed, which uses grey relational analysis algorithm to construct effective matrix of measurement data correlation from three sensors. The performances of the new algorithm and related algorithms are compared and analyzed. The results of simulation show that the proposed algorithm is respectively better than the optimal 3-D assignment algorithm based on dynamic information and the improved optimal 3-D assignment algorithm, which merely use state information to track multi-target. And the new algorithm is applicable to a wide detection scenario and has good tracking stability.

Corresponding Author: Zhaofeng Su, School of Information and Electrical Engineering, Ludong University, Yantai 264025, China
This work is licensed under a Creative Commons Attribution 4.0 International License (URL: http://creativecommons.org/licenses/by/4.0/).

INTRODUCTION OF THE IMPROVED OPTIMAL 3-D ASSIGNMENT MODEL

The optimal 3-D assignment model based on dynamic information: The optimal assignment algorithm on the basis of dynamic information constructs the-correlation probability between measurement of each single sensor and target as follows:

$$f_{it}(v_{it}) = \frac{P_D \cdot P_G \cdot \exp[-\frac{1}{2} v_{it}^{'}(k) \cdot S_t^{-1}(k) \cdot v_{it}(k)]}{(2\pi)^{1/2} \sqrt{|S_{it}|}} \quad (1)$$

where, $v_{it}(k) = z_{it}(k) - Z_t(k \mid k-1)$ is filter residual vector, P_G is gate probability, S_t (k) is residual covariance matrix.

Take above correlation probability as the correlation coefficient between measurement of each sensor and target track, fuse correlation coefficients between measurement of different sensors and target track through using grey relational analysis algorithm and then one can obtain measurement data correlation degree $c_{i_1 i_2 i_3}$ that 3-tuple of measurement $Z_{i_1 i_2 i_3} = \{Z_{1i_1}, Z_{2i_2}, Z_{3i_3}\}$ originate from the same target and further get a 3-D assignment model of measurement data correlation as follows:

$$\max_{\rho_{i_1 i_2 i_3}} \sum_{i_1=0}^{n_1} \sum_{i_2=0}^{n_2} \sum_{i_3=0}^{n_3} c_{i_1 i_2 i_3} \cdot \rho_{i_1 i_2 i_3} \quad (2)$$

Subject to:

$$\begin{cases} \sum_{i_2=0}^{n_2} \sum_{i_3=0}^{n_3} \rho_{i_1 i_2 i_3} = 1; & i_1 = 1,2,\cdots,n_1 \\ \sum_{i_1=0}^{n_1} \sum_{i_3=0}^{n_3} \rho_{i_1 i_2 i_3} = 1; & i_2 = 1,2,\cdots,n_2 \\ \sum_{i_1=0}^{n_1} \sum_{i_2=0}^{n_2} \rho_{i_1 i_2 i_3} = 1; & i_3 = 1,2,\cdots,n_3 \end{cases} \quad (3)$$

where, $\rho_{i_1 i_2 i_3}$ are binary variables. If the 3-tuple of measurement $Z_{i_1 i_2 i_3} = \{Z_{1i_1}, Z_{2i_2}, Z_{3i_3}\}$ corresponds to a real target, $\rho_{i_1 i_2 i_3} = 1$; otherwise, $\rho_{i_1 i_2 i_3} = 0$.

The improved optimal 3-D assignment algorithm: In fact, due to the complexity of the detection environment and the measurement error of sensors, the multi-dimensional assignment problem constructed by measurements from different sensors usually exists a certain model error. If the model error of the assignment problem is big, even if one gets the accurate optimal solution of the assignment problem, the correct data correlation probability will not be high. In order to decrease the model error of the multi-dimensional assignment problem, it is necessary to effectively eliminate the interference of false location points. Popp *et al.* (2001) solves the multi-dimensional assignment problem by using the idea of *m*-best algorithm solving 2-D assignment problem (Popp *et al.*, 1999). The essence is to construct effective multi-tuple of measurement set by using *m* satisfactory solutions of the multi-dimensional assignment problem and then implements the optimal point-track correlation between multi-tuple of measurement in which there may exist several fusion measurements corresponding to the same target track and target under one-to-one feasible rule. Because the optimal assignment may result in the result that several multi-tuple of measurement which correspond to the same target are assigned to different target tracks, therefore, when the dimension of the assignment problem is not very high, the algorithm cannot achieve the goal that effectively eliminates false location points and decreases the model error of the multi-dimensional assignment problem.

The improved optimal 3-D assignment algorithm considers constructing the point-track correlation degree between effective 3-tuple of measurement and target track under multiple-to-multiple feasible rule and determines correlation matching between effective 3-tuple of measurement and target track by using the optimal assignment. The details of this algorithm are described as follows.

Firstly, one gets several satisfactory solutions of the optimal assignment problem based on dynamic information by solving the problem (2-3). Since each of the components of one satisfactory solution exactly corresponds to a 3-tuple of measurement, therefore, the components of all satisfactory solutions happen to constitute of a set of effective 3-tuple of measurement. Obviously, the effectiveness of the 3-tuple of measurement depends on the quality of the satisfactory solution of the problem (2-3). For each component of every satisfactory solution, i.e., an effective 3-tuple of measurement, one considers estimating the position of target *t* that corresponds to the 3-tuple of measurement by using the following formula:

$$\begin{cases} \hat{x}_t = \sum_{s=1}^{S} \frac{x_s}{\sigma_{x_s}^2} \Big/ \sum_{s=1}^{S} \frac{1}{\sigma_{x_S}^2} \\ \hat{y}_t = \sum_{s=1}^{S} \frac{y_s}{\sigma_{y_s}^2} \Big/ \sum_{s=1}^{S} \frac{1}{\sigma_{y_s}^2} \\ \hat{z}_t = \sum \frac{z_s}{\sigma_{z_s}^2} \Big/ \sum_{s=1}^{S} \frac{1}{\sigma_{z_s}^2} \end{cases} \quad (4)$$

where, $x_s = x_t + u_s$, $y_s = x_t + v_s$, $z_s = x_t + w_s$ are, respectively the position components of target *t* detected by sensor *s*.

Take the estimate point as a fusion measurement of three sensors and then the point-track correlation probability between the 3-tuple measurement and target track can be expressed as:

$$\lambda_{jt}^{1}(k) = \exp[-\frac{1}{2}\nu_{jt}^{'}(k)\cdot S_{t}^{-1}(k)\cdot \nu_{jt}(k)]\Big/\sqrt{2\pi S_{t}(k)} \quad (5)$$

where, $j = 1,2,\cdots,m$; $t = 1,2,\cdots,T$; m is the number of effective 3-tuple of measurement in the confirmed area at time k; T is the number of targets; $\nu_{jt}(k) = z_{jt}(k) - \hat{Z}_{t}(k \mid k-1)$; $S_{t}(k)$ is the residual covariance matrix of target t; z_{jt} (k) is the jth fusion measurement of target t at time k; $\hat{Z}_{t}(k \mid k-1)$ is one step predicted measurement of target t at time k. Then the correlation matrix between 3-tuple measurement and target track can be denoted as:

$$\Lambda^{1}(k) = [\lambda_{jt}^{1}(k)], \quad j = 0,1,\cdots,m; \ t = 0,1,\cdots,T. \quad (6)$$

In general, the effective 3-tuple of measurement and target tracks are multiple-to-multiple, so the optimal assignment problem with correlation effective matrix as (6) will inevitably lead to more false correlations. Therefore, it is necessary to improve the point-track correlation probability in (6). The idea of the improvement is to increase the weight of the correlation probability of the most likely correlation matching that the 3-tuple of measurement originates from the target track. Thus, one uses the marginal correlation probability:

$$\lambda_{jt}^{2}(k) = \frac{1}{C}\left(\varepsilon_{jt}\prod_{\substack{tr=0\\ tr\neq t}}^{T}\sum_{\substack{r=0\\ r\neq j}}^{m}\varepsilon_{rtr} + \xi_{jt}\prod_{\substack{r=0\\ r\neq j}}^{m}\sum_{\substack{tr=0\\ tr\neq t}}^{T}\xi_{rtr}\right) \quad (7)$$

Instead of the general point-track correlation probability (5) and gets the marginal correlation probability matrix as:

$$\Lambda^{2}(k) = [\lambda_{jt}^{2}(k)], \quad j = 0,1,\cdots,m; \ t = 0,1,\cdots,T. \quad (8)$$

where,

$$\xi_{ji} = \lambda_{ji}^{1} / \sum_{t=0}^{T}\lambda_{ji}^{1}, \ \varepsilon_{ji} = \lambda_{ji}^{1} / \sum_{j=0}^{m}\lambda_{ji}^{1}$$

r & tr: The serial number of fusion measurement and target
C : The normalization coefficient

In comparison with the general point-track correlation probability, the marginal correlation probability considers each possible point-track correlation which may appear under multiple-to-multiple feasible rule, so it can be regarded as the weighted probability between fusion measurement and target track. By the above conversion, the weight of the correlation probability which corresponds to the most likely correlation matching that the 3-tuple of measurement originates from the target is increased, which makes the correlation matching easier to be the component of the optimal solution of the assignment problem.

IMPROVED OPTIMAL 3-D ASSIGNMENT ALGORITHM FUSING MULTI-SOURCE INFORMATION

The optimal 3-D assignment algorithm fusing multi-source information: Let us suppose that m kinds of information of n target are measured by a sensor and $X(i)$ $(i = 1,2,\cdots,m)$ is the reference sequence of target corresponding to the ith type of measurement information, $Y_{j}(i)(i = 1,2,\cdots,m; j = 1,2,\cdots,n)$ is the comparison sequence of target j from the ith type of measurement information. The correlation coefficient between X (i) and Y_j (i) is usually expressed as:

$$r_{j}(i) = r(X(i),Y_{j}(i)) = \frac{\min_{j}\min_{i}\left|Y_{j}(i) - X(i)\right| + \rho\max_{j}\max_{i}\left|Y_{j}(i) - X(i)\right|}{\left|Y_{j}(i) - X(i)\right| + \rho\max_{j}\max_{i}\left|Y_{j}(i) - X(i)\right|} \quad (9)$$

where, $\rho \in (0,1)$ is resolution coefficient and in general, the smaller the value is, the stronger the resolution ability it has.

It can be seen from (9) that $r_{j}(i) = r(X(i),Y_{j}(i))$ describe the size of the possibility that the ith type of measurement information originates from the jth target.

For the measurements of different types of information, their physical meanings are different. Therefore, the values of the reference sequences and comparison sequences are different, respectively. In order to fuse different correlation coefficients under the same dimension, it is necessary to normalize different data sequences, so as to get the correlation degree between the measurement fusing multi-source information and target through weighting calculation. Correspondingly, the grey relational degree is defined as follows:

Let μ_i be the weight of the ith type of measurement information, it is determined by its degree of importance in m types of information and there are $0 \le \mu_{i} \le 1$, $\sum_{i=1}^{m}\mu_{i} = 1$, then the grey relational degree between the fusion information and target j can be expressed as:

$$r(X, Y_j) = \sum_{i=1}^{m} \mu_i \cdot r'[X(i), Y_j(i)] \tag{10}$$

$$(i = 1,2,\cdots,m;\ j = 1,2,\cdots,n)$$

where, r' [X (i), Y_j (i)] is the standardized grey correlation coefficient.

Let us suppose that one has respectively got correlation matrix between fusion measurement and target of three sensors and they are expressed as:

$$R^s(k) = [r^s_{i_s j}(k)] \tag{11}$$

$$(i_s = 1,2,\cdots,n_s;\ s = 1,2,3;\ j = 1,2,\cdots,n)$$

where, i_s is the i_s^{th} measurement of sensor s and n_s is the measurement number of targets from sensor *s*.

Further, through analyzing measurement sequences from different sensors continuing to use grey relational analysis algorithm, one can get the size of the possibility that 3-tuple of measurement $Z_{i_1 i_2 i_3} = \{Z_{1i_1}, Z_{2i_2}, Z_{3i_3}\}$ originates from the same target, let it be $f_{i_1 i_2 i_3}$. Then the measurement data correlation problem of three sensors based on multi-source information fusion can be described as the following 3-D assignment problem:

$$\max_{\tau_{i_1 i_2 i_3}} \sum_{i_1=0}^{n_1} \sum_{i_2=0}^{n_2} \sum_{i_3=0}^{n_3} f_{i_1 i_2 i_3} \cdot \tau_{i_1 i_2 i_3} \tag{12}$$

Subject to:

$$\begin{cases} \sum_{i_2=0}^{n_2} \sum_{i_3=0}^{n_3} \tau_{i_1 i_2 i_3} = 1; \quad i_1 = 1,2,\cdots,n_1 \\ \sum_{i_1=0}^{n_1} \sum_{i_3=0}^{n_3} \tau_{i_1 i_2 i_3} = 1; \quad i_2 = 1,2,\cdots,n_2 \\ \sum_{i_1=0}^{n_1} \sum_{i_2=0}^{n_2} \tau_{i_1 i_2 i_3} = 1; \quad i_3 = 1,2,\cdots,n_3 \end{cases} \tag{13}$$

Improved optimal assignment algorithm fusing multi-source information: For getting IMFOA algorithm, one just needs to replace solving problem (2-3) in the improved optimal assignment algorithm described in this section by solving problem (12-13), then one can easily get the improved optimal algorithm based on multi-source information fusion.

Simulations:

Simulation scenarios: In the simulations, it is assumed that eight target move at a constant speed in parallel direction in a plane. The errors of the same type of measurement information of three sensors are, respectively the same; target-to-target interval is taken as a constant; Radar sampling interval is T = 2s; detection probability is $P_D = 0.95$; gate probability is $P_G = 1$; clutter coefficient is $\lambda = 2$. Select target state, the radiation source carrier frequency and pulse repetition interval to constitute of radar observation vector; RF is fixed and the center values of different targets are respectively 1000 iMHZ (i = 1, 2,…, 8), PRI is fixed and the center values of different targets are respectively 0.1 i *ms* (i = 1, 2,…, 8). The number of simulation steps is 150 and the number of simulation times is 50.

SIMULATION RESULTS ANALYSES

In order to verify the effectiveness of the proposed algorithm, performance comparisons of IMFOA algorithm, OA algorithm and IOA algorithm under conditions of different measurement errors are shown as follows:

- When target-to-target interval is $\tau = 500$ m, measurement errors of different feature information are, respectively $e_{RF} = 1$ MHz and $e_{PRI} = 0.03$ ms, the comparisons of the Root-Mean-Square Error (RMSE) of different algorithms are as follows.
- When target-to-target interval is $\tau = 200$ m, measurement errors of different feature information are respectively $e_{RF} = 0.5$ MHz and $e_{PRI} = 0.003$ ms, comparisons of RMSE of different algorithms are shown as follows.
- When target-to-target interval is $\tau = 200$ m, measurement errors of different feature information are, respectively $e_{RF} = 1$ MHz, $e_{PRI} = 0.03$ ms, comparisons of RMSE of different algorithms are shown as follows.

As can be seen from Fig. 1 and 2, when target-to-target interval is not big or measurement error is small, the performances of OA and IOA algorithms have little difference. The reason is that in general detection environment, the model error of OA algorithm is small; in this case, IOA algorithm cannot better play the performance advantage that can decrease the model error of assignment problem of point-track correlation. And IOA algorithm is an algorithm which is more applicable for dense targets and clutter environment. This conclusion can be verified in Fig. 3.

As can be seen from Fig. 4 to 6 that IMFOA algorithm is superior to IOA algorithm under different simulation scenarios and from Fig. 1 to 6, it is also can be seen that IMFOA algorithm is much better than OA

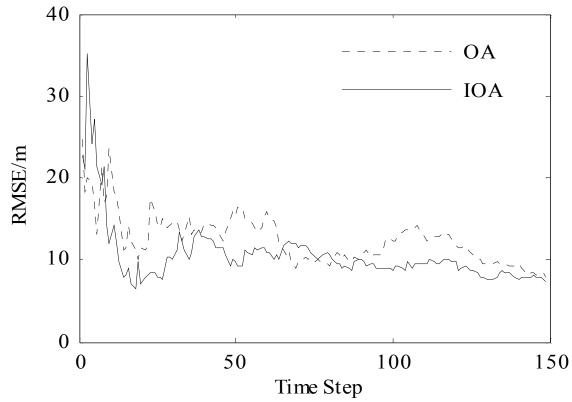

Fig. 1: Comparisons of RMSE of OA and IOA under condition of $e_r = 200$ m, $e_\theta = 0.02$ rad

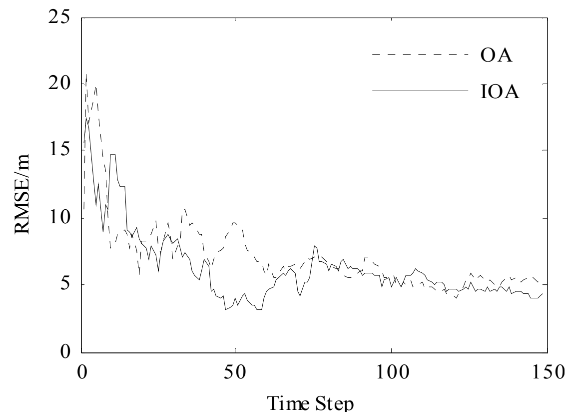

Fig. 2: Comparisons of RMSE of OA and IOA under condition of $e_r = 100$ m, $e_\theta = 0.01$ rad

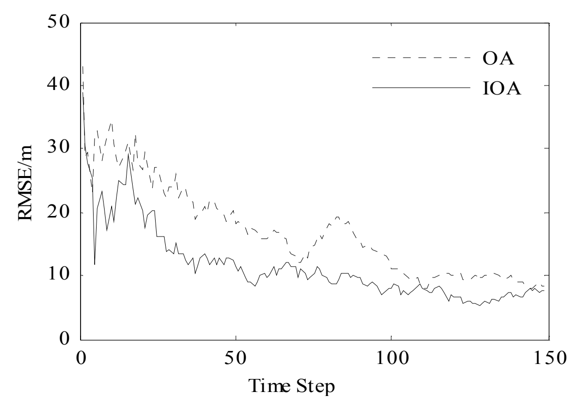

Fig. 3: Comparisons of RMSE of OA and IOA under condition of $e_r = 100$ m, $e_\theta = 0.01$ rad

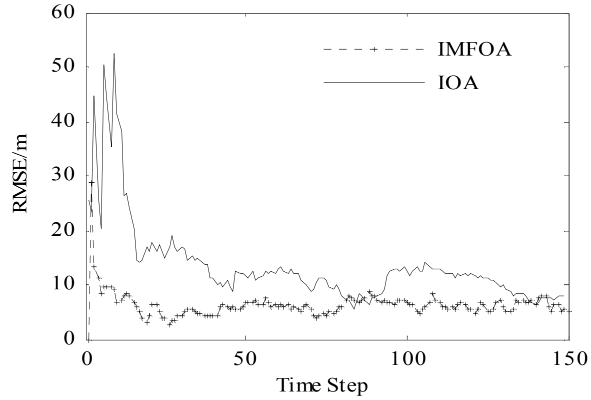

Fig. 4: Comparisons of RMSE of IOA and IMFOA under condition of $e_r = 100$ m, $e_\theta = 0.01$ rad

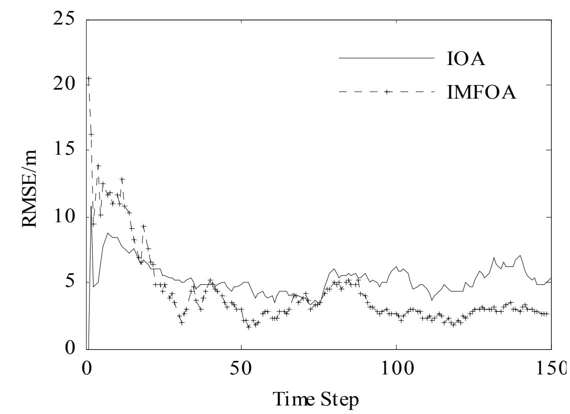

Fig. 5: Comparisons of RMSE of IOA and IMFOA under condition of $e_r = 100$ m, $e_\theta = 0.01$ rad

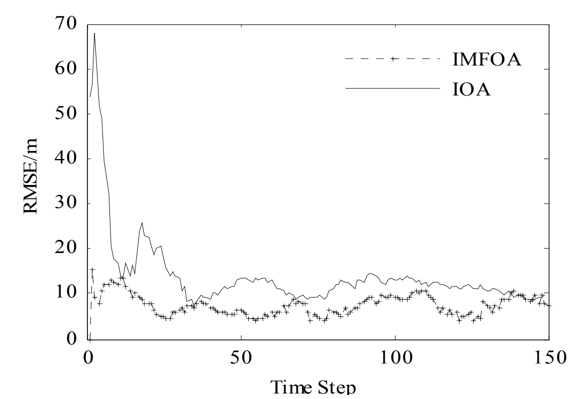

Fig. 6: Comparisons of RMSE of IOA and IMFOA under condition of $e_r = 200$ m, $e_\theta = 0.02$ rad

algorithm. This is because that IMFOA algorithm based on multi-source information fusion not only improves the quality of the satisfactory solutions of OA algorithm by effectively fusing multi-feature information, but also has the performance advantage of IOA algorithm, which is suitable for tracking multi-target in dense targets and clutter scenario. Therefore, whether in general or poor detection scenario, IMFOA algorithm plays better performance in multi-target tracking.

In comparison with OA algorithm which is more suitable for general detection scenario and IOA algorithm which is only applicable to worse detection scenario, MFOA algorithm has the advantage of a wide application range and stable tracking performance and is an effective multi-target tracking algorithm.

CONCLUSION

In view of the data association algorithms of multi-sensor multi-target tracking system, an improved optimal assignment algorithm based on multi-source information fusion is proposed. Firstly, the improved algorithm fuses multi-source information through using grey relational analysis algorithm to get the correlation degree between fusion measurement of single-sensor and target track. Secondly, the effective function of measurement data correlation of three sensors can be got through analyzing the fusion measurement sequences from different sensors through continuing to use grey relational analysis algorithm. Finally, the improved optimal assignment algorithm fusing multi-source information is got by effectively weighting the point-track correlation probability under multiple-to-multiple feasible rule. Simulation results show that compared with OA algorithm and IOA algorithm, IMFOA algorithm improves the accuracy of multi-target tracking in varying degrees under different simulation scenarios and is a stable multi-target tracking algorithm.

REFERENCES

Han, C.Z., H.Y. Zhu and Z.S. Duan, 2010. Multi-Source Information Fusion. Tsinghua University Press, Beijing.

Pan, Q., X.N. Ye and H.C. Zhang, 2005. Generalized probability sata association algorithm. Acta Electron. Sinica, 33(3): 467-472.

Pan, Q., Y. Liang, F. Yang and Y.M. Cheng, 2009. Modern Target Tracking and Information Fusion. National Defense Industry Press, Beijing.

Popp, R., K. Pattipati and Y. Bar-Shalom, 1999. Dynamically adaptable m-Best 2D assignment algorithm and multi-level parallization. IEEE T. Aerospace Electron. Syst., 35(4): 1145-1160.

Popp, R., K. Pattipati and Y. Bar-Shalom, 2001. M-best S-D assignment algorithm with application to multitarget tacking. IEEE T. Aerospace Electron. Syst., 37(1): 22-39.

Wang, J.G. and J.Q. Luo, 2004. Passive tracking based on data association with information fusion of multi-feature and multi-target. Acta Electron. Sinica, 32(6): 1013-1016.

Wang, J.G., J.Q. Luo and X.M. Jin, 2006. Probabilistic data association algorithm of passive tracking based on information fusion with gray correlation analysis. Acta Electron. Sinica, 34(3): 391-395.

Xu, Y., F. Yang and Q. Pan, 2005. Generalized probability data association algorithm. Comput. Measur. Control, 13(11): 1263-1265.

Zhang, J.W., Y. He and W. Xiong, 2007. Centralized multisensor fuzzy joint probabilistic data association algorithm. J. Tsinghua University, 47(7): 1188-1192.