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Co-optimization of sensor fusion and control strategies in electrical and electronic systems

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Abstract. In multi-sensor fusion, resource scheduling and control is responsible for rationally assigning multiple sensors in a networked system to the tasks faced by the system, and is the key to improving the quality of information fusion, increasing the overall system effectiveness, and obtaining the best observation results. Resource scheduling control is mainly to determine which sensors are selected to monitor and track the target according to certain optimization criteria, as well as the working mode, parameters, and measurement process of the sensors, and also to determine how the sensors can cooperate with each other and how the sensors can be adapted to the environment, and so on. This paper is to study the resource scheduling and control algorithm based on covariance control, so as to optimize the sensor resource scheduling and control.

Keywords: multi-sensor fusion, sensor scheduling, sensor resources.

1. Introduction

Multi-sensor fusion is the monitoring and tracking of targets in the surveillance area by means of networking, which has been widely used in air traffic control, air defense surveillance and other fields. Commonly used sensors are: radar (RA), secondary radar (SSR), enemy and self recognizer (IFF), photoelectric infrared (IF), etc. The main purpose of sensor resource scheduling and control is to make full use of these sensors to collect relevant information to satisfy the all-around surveillance and tracking of multiple targets, or to get the optimal metrics (such as probability of detection, trajectory accuracy, etc.) for a specific characteristic required by the system to scientifically control the sensor resources by this optimal criterion. This optimization criterion is used to allocate the sensor resources in a scientific and reasonable way. Another purpose of sensor resource scheduling and control is to realize the overall optimization of the multi-sensor system, by checking the interrelationship between the tracking situation and the demand criteria to generate a feedback, and continuously adjust and control the sensor work. Through the resource scheduling control of different characteristics and functions of the sensor to take full advantage of multiple sensors or the advantages of their respective operations, you can improve the effectiveness of the multi-sensor fusion system, resource scheduling control is the core of the multi-sensor data fusion system in the use and management of multi-sensor data fusion system to achieve the goal of the target monitoring system, the target characteristics of the main way to obtain. It is mainly through the optimal allocation of resources within the multi-sensor data fusion system. Through unified resource scheduling, a collaborative detection mode is formed, more resources are focused on key observation areas and targets, and more attention is paid to key targets while taking into account regional

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surveillance. Evaluate the utilization of multi-sensor resources, form an optimized method and effective strategic layout, provide guidance methods for optimization and deployment, and enhance the effectiveness of the system; in terms of system control, consider the change of discovery probability, collaborative detection, human intervention, and other factors, and carry out the integrated management of system detection and collaborative control; resource control is mainly based on the guidance information of the command center, human control commands, and target posture information, to complete the control of sensor resources, and to ensure that the system can be used in a timely manner. Resource control is mainly based on the guidance information, human control commands, and target posture information of the command center to complete the task allocation, work mode and resource scheduling of the sensor resources.

Adopting the strategy based on covariance control to optimize the resource scheduling control, the first is to pre-set a desired tracking accuracy for the target observed by the sensors, i.e., desired covariance matrix, and then control the sensors to make the actual covariance approximate the desired covariance in some sense in some metrics and criteria of the system, this is a general optimization model, which can be expressed by the following form of resource allocation model.

2. Resource allocation optimization model

In the process of multi-sensor observation of targets, it is assumed that the expected covariance matrix is set for D known observed targets as $p_0^i, (i = 1,2,3,\ldots\ldots D)$,The control vector for the sensor is $U(t_k) = \{u(t)\} \mid u(t) = 0,1,2,\ldots. D; t = t_1, t_2 \ldots t_k\}$。Where u(t) denotes the working mode used by a certain sensor working at moment t u(t)=0 indicates that the sensor is performing a search task; u(t)=j indicates that the jth target is being tracked, then the optimal control model for resource scheduling and control in the process of observing the target by multiple sensors can be set up as follows [1]:

$$u(t_{k+1}) = j_0(t_{k+1}) = \arg_{\min} F[p_0^i, p^i(t_{k+1} \mid U(t_k), u(t_{k+1}) = j), i = 0,1,2,\ldots\ldots D]$$

included among these $p^i(t_{k+1} \mid U(t_k), u(t_{k+1}) = j$ denotes the tracking error covariance matrix of the ith target at the moment tk+1 under the condition that the sensor is known to be tracking the ith target at that moment, and F is the metric function for calculating the deviation of the two sets of matrices. The above formula indicates that the criterion for the selection of the working mode of the sensor at the next moment is to make the tracking error covariance of all the targets closest to its desired covariance set under some metric criterion, that is, when the value of the [F] function is taken to be the smallest, it is the principle of the sensor resource scheduling and control. The specific representation of the function F can be further refined into two resource allocation criteria, i.e., the criterion of minimizing the maximum covariance deviation and the criterion of minimizing the mean value of the covariance deviation, which are hypothetically denoted as the F-1 criterion and the F-2 criterion [2].

For the F-1 criterion, the expression of the sensor resource allocation optimization management model is:

$$u(t_{k+1}) = j_0(t_{k+1}) = \arg_{\min}[\max f\, p_0^i, p^i(t_{k+1} \mid U(t_k), u(t_{k+1}) = j)]$$

For the F-2 criterion, the expression of the optimal management model for sensor resource allocation is:

$$u(t_{k+1}) = j_0(t_{k+1}) = \arg_{\min}[\frac{1}{D} f\, p_0^i, p^i(t_{k+1} \mid U(t_k), u(t_{k+1}) = j)]$$

where the function f(A,B) denotes the dissimilarity measure between matrix A and matrix B, which can be selected in a number of different matrix representations as needed. The general optimization model for sensor resource allocation described above is not limited by the number of dimensions of the state estimates of individual targets in the surveillance area and the number of targets to be tracked, since the core basis of this optimization model is to preset a desired tracking accuracy, i.e.,[3] a desired covariance matrix, and then allocate the sensor resources in the grouping according to some metric criterion that is chosen. Suppose that the most recent filtered update states of the D observed targets prior to the long moment are known to be:

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$$\{t_{k(i)}, p^i t(k_{(i)})\}, (t(k_{(i)} < t_k),$$

where the k(i) subscript denotes the discrete ordinate of the kth filtering for the ith target.

Assume that the discretized equation of state for the ith target is:

$$x^i(t_{k+1}) = F^i(T_k^i)x^i(t_{k(i)}) + G^i(T_k^i)W^i(T_k^i)$$

where $x^i(t_{k(i)})$ represents the state vector of the ith target at the moment. $W^i(T_k^i)$ is the white noise vector of the system with covariance matrix $Q^i(T_k^i)$, $F^i(T_k^i)$ is the state transfer matrix at the period tk, $G^i(T_k^i)$ is the input matrix at the moment tk, and $T_k^i = t_{k+1} - t_{k(i)}$ is the sampling interval of this target for the moment tk+1.

The measurement equation of the system is:

$$Z^i(t_k) = H^i x^i(t_k) + v^i(t_k)$$

where $Z^i(t_k)$ denotes the measurement vector of the radar system for target i at moment tk, $v^i(t_k)$ is the measurement noise whose covariance matrix is $R^i(t_k)$, $H^i(t_k)$ is the observation matrix, and the noise $W^i(T_k^i)$ is relatively independent of $v^i(t_k)$ and is independent of the $x^i(t_k)$ initial state.

Let the filter covariance and prediction covariance array in the filtering algorithm be $P^i(t_{k+1})$ and $P^i(t_{k+1}^-)$,, respectively, and the sensor control vector be $\mathrm{U(t_k)} = \{\mathrm{u(t)}\} \mid \mathrm{u(t)} = 0,1,2,\ldots.\mathrm{D}; \mathrm{t} = \mathrm{t_1}, \mathrm{t_2} \ldots \mathrm{t_k}\}$. The tracking error covariance matrix of each target at moment tk+1 can be expressed as:

$$\mathrm{p^i(t_{k+1} \mid U(t_k), u(t_{k+1}) = j)} = \begin{cases} P^i(t_{k+1}), i \neq j \\ P^i(t_{k+1}^-), i = j \end{cases}$$

From the above equation tk+1, we can derive the error covariance matrix of all observation targets at the moment, which is brought into the sensor resource allocation model, and according to the current tracking state of the sensors and the expected covariance index [4], we can derive the form of resource allocation of the sensors at the next moment, so as to re-execute the resource scheduling control.

3. The matrix metric function selection

Comparing the difference between two matrices has a variety of metrics, often used matrices are column paradigm, 2-paradigm, Frobenius paradigm, matrix trace, determinant, and matrix singular value decomposition and so on. Comparing the variability between the actual covariance and the expected covariance array can be considered using the above matrix metrics.

Definition of Matrix Metric: A set X∈R is a linear space mapping $: \mathrm{X} * \mathrm{X} \rightarrow \mathrm{R}, \forall \mathrm{A}, \mathrm{B} \in \mathrm{X}$. over the number field illumination. f is said to be a matrix metric on a set X if the f mapping satisfies:(1) symmetry: f(A,B)=f(B,A); and (2) non-negativity: f(A,B)≥0. Thus the singular value decomposition of the matrices listed above, as well as the paradigm, trace, etc., can be used as a measure of the variability of the covariance matrices. Assuming two covariance matrices P1P2,, due to the covariance matrix has non-negative and symmetric properties available P1 = PT ≥ 0 and B2 = P2T ≥ 0 two representations of the situation, assuming that the difference between these two matrices is △P = [△P][5], there is a △P = P1-P2, without loss of generality, you can select the 2-paradigm of the matrix and the absolute value of the traces of the two matrix measures for the following analysis, the definition of the two matrix measures can be expressed as follows.

Table 1. Comparison of Matrix Properties and Metrics between P1 and P2

Matrix Property/Metric	P1	P2	ΔP = P1 - P2
Matrix Dimension	n x n	n x n	n x n
Trace	Tr(P1)	Tr(P2)	ΔTr
Determinant	det(P1)	det(P2)	Δdet
2-Norm	‖P1‖2	‖P2‖2	‖ΔP‖2
Singular Value Decomposition	σ1(P1)	σ1(P2)	Δσ1 = σ1(P1) - σ1(P2)
Matrix Norm Difference	‖P1‖F	‖P2‖F	‖ΔP‖F

M-l metric: absolute value tracing.

$$f(P_1, P_2) = \text{trace}[\text{abs}(\triangle P)] = \sum_{i=1}^{n} |\triangle P_{ii}|$$

M-2 metric: Matrix 2-paradigm:

$$f(P_1, P_2) = \left||\triangle P|\right|_2 = \left||P_1 - P_2|\right|_2$$

When comparing the difference between the expected covariance and the actual covariance, the choice of matrix metrics is not limited to the variability metrics of the two matrices, but can be flexibly selected for the working modes and parameters of the sensors in the group network, etc [6].

4. Conclusion

This paper describes the study of resource scheduling control in multi-sensor fusion based on covariance control strategy, and describes the resource optimization in multi-sensor fusion system under the premise of maintaining the target covariance in the range of desired covariance, and utilizing the characteristics of different sensors according to the system needs to carry out resource management control for multiple sensors. Using the advantages of multiple sensors with different characteristics, the network can improve the spatial resolution and target discovery probability in a large surveillance area as much as possible, and can also treat all the tracked targets in its surveillance area differently, such as concentrating more resources on the key observation area and the key observation targets, and paying more attention to the key targets while taking into account the regional surveillance.

Authors contribution

The two authors contributed equally to this paper.

References

[1] Du Wei,Wang Yu,Meng Linan. Security distribution system of experimental center based on sensor data fusion[J]. Electronic Fabrication, 2023, 31(24):66-70.

[2] LU Xiuli, HU Tianyu, Jisong, et al. Research on wireless sensor network positioning based on improved bat optimization algorithm[J]. Foreign Electronic Measurement Technology, 2023, 42(6):103-109.

[3] WU Yao,ZHU Nongtai. Multi-sensor fusion method for lane lines based on graph optimization,system,electronic device:CN202211616852.4[P].CN115984654A[2024-06-05].

[4] Y. J. Zheng,X. D. Liu,T. Zhou,et al. Research on optimization strategy of robotics and automation technology in process intelligent upgrading[J]. Manufacturing Automation, 2023, 45(10):216-220.

[5] Dai Liang, Zhang Jinlong, Qin Wen. Optimization strategy of roadside unit transfer control for transportation energy integration[J]. Control and Decision, 2023, 38(12):3354-3362.

[6] M. J. Beschooner, J. D. Spetzinger, Shogo Tada, et al. Method and system for controlling fluid pressure in a machine using sensor fusion feedback.CN201810614298.3 [2024-06-05].