A multi-sensors pure azimuth data fusion method

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Abstract—Passive detection sensors have the advantages of good concealment, strong viability, strong resistance to electronic interference, wide coverage of airspace, and stronger detection capabilities for low-altitude targets than active detection sensors, and farther detection distances. It has caused more and more research and application attention in various fields. However, passive detection sensors mainly obtain azimuth information, no stable distance information, and stable tracking of only azimuth targets has many uncertainties. In recent years, how to integrate effective and stable passive detection data has become the focus of scholars research and the difficulty of urgent breakthrough. This article proposes a method of fusion of pure azimuth data for systems with multi-source detection sensors, through the filtering of "modified extreme coordinates" based on the measurement results of each sensor, "based on the Lagrange daily linear interpolation method" time allocation, "m/n logic-based" track association and fusion, obtain more accuracy and track more stable direction measurement results, and improve the comprehensive capabilities of the multi-source detection sensor system.

1. INTRODUCTION
Passive sensors have advantages such as good concealment, strong viability, strong resistance to electronic interference, wide airspace coverage, and strong low-altitude detection capability compared to active detection sensors, and far detection distance, but the data obtained by passive sensors are mainly Bearing information has many uncertainties in the integration of pure azimuth information. In recent years, how to carry out effective and real-time passive detection data integration has become the focus and difficulty of scholar research.

A system with multiple passive detection sensors, which can take advantage of the different characteristics of inaccessible type sensors, can obtain information on different attributes of the target in multiple places, and can bring many performance benefits. This article is aimed at systems with multi-source probe sensors, proposed a combination method for pure azimuth data, which can effectively improve the detection accuracy and stability of the target azimuth.

2. THE OVERALL STRUCTURE OF THE MULTI-SENSORS PURE AZIMUTH FUSION METHOD
This method first filters the measurement results of each sensor with the "modified extreme coordinates" , secondly the time allotment of the data obtained by the multi-sensors with the "lagrange linear interpolation method", and finally the trajectory correlation and fusion of the data obtained by different sensors with the " m/n logic" , to obtain higher accuracy and stable tracking direction results. The principle box diagram of this method is shown in Figure 1.
3. Pure Bearing Tracking Filter

3.1 State Equation

In pure azimuth tracking, due to the nonlinearity and observability of the essence of the tracking system, it caused difficulties in the processing of the tracking algorithm and caused the tracking results to contradict the accuracy and convergence time. Filtering based on the revised extreme coordinates (MPC) resolved the contradiction well.

Select $\phi$, $\dot{\phi}$, $r / r$ be the state variable, $\phi$ which is the azimuth angle, $r$ is the distance from the target distance sensor, the state vector in the MPC is

$$Y(k) = [y_1(k) \quad y_2(k) \quad y_3(k)]' = [\phi(k) \quad \dot{r}(k)]'$$

(1)

the available state equation is

$$Y(k+1) = f[Y(k);(k+1)T,kT] = 
\begin{bmatrix}
    y_1(k) + arctan(s_y(k) / s_x(k)) \\
    \frac{s_2(k)}{s_1(k)} \\
    \frac{s_3(k)}{s_4(k)}
\end{bmatrix}$$

(2)

among them

$$s_1 = y_1(k), \quad s_2 = y_2(k), \quad s_3 = T_y(k), \quad s_4 = 1 + T_y(k)$$

(3)

when the pure azimuth is passively tracked, because there is only the measured value of the azimuth angle, the measurement equation can be expressed as

$$Z(k) = H(k)Y(k) + W(k)$$

(4)

in the formula, $Z(k)$ is the measured value; $H(k)$ is the measured matrix; $W(k)$ is the the white Gauss noise for the zero average value of the covenant difference matrix $R(k)$, that is

$$H(k) = [0 \quad 0 \quad 1]$$

(5)

$$E[W(k)] = 0$$

(6)

$$E[W(k)W'(j)] = R(k)\delta_{ij} = \sigma^2\delta_{ij}$$

(7)

3.2 Filter Model

The state-step forecast is

$$\hat{Y}(k+1) = f[\hat{Y}(k | k);(k+1)T,kT]$$

(8)

the state forecast co-sponsored matrix is

$$P(k+1 | k) = A(k+1 | k)P(k | k)A'(k+1,k)$$

(9)

in the formula, the state transfer matrix is

$$A(k+1,k) = \frac{\partial f[\hat{Y}(k | k);(k+1)T,kT]}{\partial Y(k | k)}$$

(10)

the co-operation difference is

$$S(k+1) = H(k+1)P(k+1 | k)H'(k+1) + R(k+1)$$

(11)
the filter gain is
\[ K(k+1) = P(k+1|k)H'(k+1)[S(k+1)]^{-1} \] (12)
the status update equation is
\[ \hat{Y}(k+1|k+1) = \hat{Y}(k+1|k) + K(k+1)[Z(k+1) - H(k+1)\hat{Y}(k+1|k)] \] (13)
the co-operative difference update equation is
\[ P(k+1|k+1) = [I - K(k+1)H(k+1)]P(k+1|k) \] (14)
in the formula, I is the unit matrix.

4. TIME ALLOCATION
If the accuracy of each sensor is not the same, the time allotment of the sensor data with low accuracy is based on the sensor with high accuracy. If the accuracy of each sensor-like, the sensor close to the target is used as the benchmark, and the sensor data far away from the target is time-allocated. This algorithm uses time allocation based on Lagrange's linear interpolation method, the steps are as follows:

1) Assume that the first measurement data of the two sensors is the same-time, that is, TL1=TH1, as shown in Figure 2.

2) Estimate the moment corresponding to the subsequent interpolation point of the low-precision sensor. At this time there are three more situations:
   a) If the time difference between the insertion point of the low-precision sensor and its pre-sampling time is less than the low-precision sensor sampling interval, then extrapolation is based on the pre-temporal data of the low-precision sensor. For example, the data corresponding to the measurement data of the low-precision sensor and the sensor TH2 moment measurement data should be:
   \[ X_{LH2} = X_{L1} + V_{L1}(T_{H2} - T_{L1}) \] (15)
in the formula, \( V_{L1} \) is speed.

   b) If the time difference between the insertion point of the low-precision sensor and its previous-participating sampling time is greater than the sampling interval of the low-precision sensor, extrapolation is carried out on the basis of the data at the interior interpolation point closest to the internal insertion point in front of the low-precision sensor. The data corresponding to the measurement data should be
   \[ X_{LH4} = X_{L3} + V_{L3}(T_{H3} - T_{L2}) \] (16)
c) If the time difference between the corresponding moment of the interpolation point of the low-precision sensor and its previous-participating sampling moment is equal to the low-precision sensor sampling interval, keep the data of the low-precision sensor at that time unchanged, for example
\[ X_{LH4} = X_{L3}; \]
3) By analogy, two sensor data with different measurement accuracy are synchronized in time to form the target observation data of different sensors at the same time-moment.

5. RELATED FUSION
5.1 Calculation of Relevance
For the problem of lack of target location information, a purely azimuth navigation connection method based on the distance of the unit dot set is adopted. Calculate the distance between the two tracks \( d_j(k) \) while engraving coordinates.
\[ r_p(i, j) = \frac{1}{1 + \frac{1}{N_0} \sum_{i=1}^{N_0} j_{p(i,k)}} \]  

(17)

calculate the correlation coefficient.

### 5.2 Related Rules

The estimated vector \( \hat{X}_{(k|k)} \) and \( \hat{X}_{(k|k)} \) of the moment of \( k \) state is obtained by the sensor 1 to the target \( i \) and sensor 2 to the target \( j \) filter, among them the \( x, y, z \) axle position element can construct the inspection statistics \( \lambda(k) \) or correlation degree \( r_{ij}(k) \).

If \( \lambda(k) \) lower than the set inspection door limit \( T \) or higher than the set door limit, the \( i \) target voyage of sensor 1 and the \( j \) target voyage of sensor 2 at that time shall be judged from the same-target. If \( m \) of the \( n \) trajectory related judgments is to meet the gate limit requirement, then judge that the \( i \) track of sensor 1 and the \( j \) track of sensor 2 come from the same-target, and then merge the two trajectories; otherwise, the right movement of the sliding window Continue to judge the connection of the trajectory.

After calculating the correlation degree of the two trajectories from the previous calculation, the correlation matrix of the two sensor trajectories at the time of \( k \) can be constructed to establish a 2-dimensional distribution model with the target function of \( \hat{X}_{(k|k)} \) statistics and \( L(k) \) as the target function to solve the overall optimal trajectory correlation relationship:

\[ L(k) = \max_{\eta} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \eta_i r_{ij}(k) \]  

(18)

\[ \sum_{j=1}^{n_2} \eta_j = 1 \quad \forall i = 1, 2, \ldots, n_1 \]

\[ \sum_{i=1}^{n_1} \eta_i = 1 \quad \forall j = 1, 2, \ldots, n_2 \]  

(19)

Among them, \( \eta_i \) is a binary variable. When reference trajectory \( X_i \) is associated with comparative trajectory \( X_j = 1 \), otherwise: \( \eta_i = 0 \). When all sensor observation tracks come from a common observation target, the correlation relationship obtained by the 2D distribution processing is the final correlation result; but when each sensor has a non-common observation target, the correlation management obtained by the 2D distribution processing also needs to go through the gray correlation gate \( \varepsilon \), \( 0.5 \leq \varepsilon < 1 \)'s test, that is, the correlation right of the gray correlation above the door limit, was confirmed as the trajectory association. \( \varepsilon \)'s value can be determined by simulation. When the problem is extended to the trajectory connection problem of more than 3 sensors, a multi-dimensional distribution model can be established to construct the overall statistical volume:

\[ \hat{\lambda}_{(k_1,\ldots,k_m)} = \sum_{k=1}^{M} r_{ij}(k) \]  

(20)

Similar to the definition of binary variable \( \mu_{(k_1,\ldots,k_m)} \), when reference trajectory \( X_i \) is associated with comparative trajectory \( X_j = 1 \); otherwise \( \mu_{(k_1,\ldots,k_m)} = 0 \). In this way, a multi-dimensional distribution model with \( \hat{\lambda}_{(k_1,\ldots,k_m)}(k) \) as the statistical quantity and \( L(k) \) as the target function can be established to understand the overall optimal navigation correlation of more than 3 sensors:

\[ L(k) = \max_{\mu_{(k_1,\ldots,k_m)}} \sum_{k=1}^{M} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mu_{(k_1,\ldots,k_m)} \lambda_{(k_1,\ldots,k_m)}(k) \]

\[ \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mu_{(k_1,\ldots,k_m)} = 1 \quad \forall k = 1, 2, \ldots, M \]

\[ \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mu_{(k_1,\ldots,k_m)} = 1 \quad \forall k = 1, 2, \ldots, M \]

\[ \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mu_{(k_1,\ldots,k_m)} = 1 \quad \forall k = 1, 2, \ldots, M \]

\[ \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mu_{(k_1,\ldots,k_m)} = 1 \quad \forall k = 1, 2, \ldots, M \]  

(21)

(22)
5.3 The Trajectory Fusion

After the trace of sensor 1 is associated with the track of sensor 2, the following co-differential weighted average method can be used for fusion, that is

\[
P(k | k) = \left\{ \left[ P'(k | k) \right]^{-1} + \left[ P''(k | k) \right]^{-1} \right\}^{-1}
\]

\[
\hat{X}(k | k) = P(k | k)^{-1} \hat{X}(k | k) + \left[ P_{ij}(k | k) \right]^{-1} \hat{X}_{ij}(k | k)
\]

6. Simulation Analysis

Simulate the pure azimuth filter algorithm and set the model as follows: the passive detection sensor coordinates are (0km,0km), the target initial position is (30km,50km), the angle of movement direction and the north-south direction is 300°, the speed is 28 knot, sensor angle error 1°, sampling interval \(A T = 0.5s\). After 100 Monte Carlo simulation experiments, the simulation results are shown in Figure 3. The average value of data before filtering is 1.015°, after filter is 0.55°, the accuracy is increased by about 46%.

Hypothesis there are two passive detection sensors on each platform, the simulation target is evenly distributed in the rectangular area of 400km×400km, which contains 30% of the target, and its height is evenly distributed between 7km-20km. The speed of the sea target is evenly distributed between 4-140m/s, the speed of the air target is evenly distributed between 55-580m/s, the course is evenly distributed between \([0,2\pi]\), and the target speed is straight or turned. Assuming that the platform is located in \((0,0)\), since the passive detection sensor can only observe the azimuth information of the target, the azimuth information is projected on the unit ball to indicate that the picture below is a simulation scene of 5 goals and 50 goals.

Figure 3 motion view (5 goals)

Figure 4 motion perspective (5 goals)

Figure 5 motion view (50 goals)

Figure 6 motion perspective (50 goals)

Figure 7 Real bearing (5 goals)

Figure 8 Real bearing (50 goals)
The measured accuracy of the two passive detection sensors is set at 2° (root mean square value) and 3° (root mean square value), and the observation results of the target azimuth are shown in the figure below.

![Figure 9](image1.png) 5 target measurement information

![Figure 10](image2.png) 50 target measurement information

According to the algorithm steps above, the simulation results are shown in Table 1.

| Serial number | Actual target number | Background target number | Fusion time (s) | Correct rate |
|---------------|----------------------|--------------------------|-----------------|--------------|
| 1             | 5                    | 20                       | 0.32            | 87.50%       |
| 2             | 5                    | 30                       | 0.72            | 84.17%       |
| 3             | 5                    | 40                       | 1.30            | 81.25%       |
| 4             | 5                    | 50                       | 1.93            | 78.20%       |
| 5             | 10                   | 20                       | 0.38            | 92.80%       |
| 6             | 10                   | 30                       | 0.70            | 90.03%       |
| 7             | 10                   | 40                       | 1.15            | 88.01%       |
| 8             | 10                   | 50                       | 1.91            | 85.10%       |
| 9             | 20                   | 20                       | 0.37            | 93.30%       |
| 10            | 20                   | 30                       | 0.65            | 94.10%       |
| 11            | 20                   | 40                       | 1.38            | 91.50%       |
| 12            | 20                   | 50                       | 1.79            | 90.92%       |

7. CONCLUSION

Using the MPC pure azimuth filtering method, the preliminary pure azimuth data obtained by each sensor is processed to form a pure azimuth track information with higher accuracy. The typical data simulation results in an accuracy increase of about 40% to provide higher quality for subsequent data integration Source information. Through time alignment and association integration, the pure azimuth information obtained by the multi-sensor is integrated. Through simulation analysis, under complex target background conditions, the method is used to integrate short time and high fusion accuracy rate, which can effectively improve the multi-source detection sensor system Comprehensive processing capability.

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