Receiving and Fusion Processing of Space Reconnaissance Data Based on Multisensor

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Abstract. In the coming information age, intelligent reconnaissance and comprehensive analysis of communication targets in the electromagnetic signal environment of space areas is an important aspect of obtaining space information rights. In the future, the reconnaissance of space communication targets will be characterized by large data capacity, multiple sources, and high correlation. At the aeronautical information processing center, all reconnaissance data is not allowed to be continuously and simply accumulated. It is necessary to carry out effective fusion processing and intelligence integration to form a clear, reliable and complete intelligence description of the state of communication targets. The purpose of this paper is to receive and fuse multi-sensor-based space reconnaissance data. In terms of method, this paper mainly analyzes the start of the trajectory, and then analyzes the error registration of the sensor. The sources of sensor system error include: distance error, azimuth error, elevation error, time error and position error. The sensor has time alignment and spatial error recording. Through wavelet threshold denoising and Kalman filtering, the obtained information is more complete. In terms of experiments, after analyzing the observation accuracy of each sensor and eliminating the relative deviation, data fusion and processing are performed. Data preprocessing includes coordinate transformation, outlier elimination and data compression. Four aircraft and three sensors are analyzed: radar sensor SAR, infrared sensor IR and photoelectric sensor EO. Finally, it is concluded that the effectiveness and fault tolerance of the data are significantly improved after the data fusion.

Keywords: Electromagnetic Signals, Space Communications, Reconnaissance Data, Sensor Systems

1. Introduction

With the rapid development of aerospace technology, the application of aerospace technology in the military and civilian fields is becoming more and more widespread. Because its control mainly depends on measurement and control system in aerospace, real-time measurement and display of flight track data is one of the first tasks of measurement and control system. With the continuous enrichment and improvement of measurement and control methods, multi-station tracking and mixed tracking of
different measurement systems have become the main methods of measurement and control. Therefore, the flight path tracking measurement of modern aircraft is a typical application field of multi-sensor measurement information fusion technology. Develop a real-time data fusion processing system that can comprehensively make use of a large amount of redundant and complementary diversified track measurement information provided by multiple sensors in the aircraft measurement and control system, improve the ability to capture, track and identify targets, and enhance the reliability of the entire system And robustness, expand the time and space coverage of the entire measurement and control system, improve the accuracy and credibility of the system's real-time data processing, and provide a scientific and reliable basis for command and control in aircraft flight operations.

Space reconnaissance is a military activity that uses various aircraft as platforms and carries reconnaissance equipment to perform valuable targets on the ground, in the air, and in space, and to perform reconnaissance and surveillance [1]. Space reconnaissance has become the main source of strategic information due to its advantages, including high orbit, wide reconnaissance range, fast target, and unlimited restrictions on borders and geographical conditions. In addition, it has expanded to the scope of war and tactics, the world's major military powers and space powers have fought and developed, and have become the focus of space competition [2]. However, the single-head sensor system has a long target revisit period, poor real-time information acquisition, and once the trajectory changes and maneuver becomes difficult, the enemy predicts the rules of battle and evacuates or hides. There are issues such as taking action, and with the development of space information attack and defense system technology, the survivability of single-beam sensor systems is threatened. Therefore, we should focus on the development of multi-sensor information systems to improve the single-beam sensor information system and meet the information reconnaissance capability requirements of future joint operations. Space reconnaissance plays a vital role as a national strategic reconnaissance tool in modern reconnaissance surveillance. With the improvement of space reconnaissance information in real time, the ability to perform tactical and operational reconnaissance is increasing, and the dependence of modern wars on space reconnaissance is also increasing [3]. According to statistics, current space reconnaissance accounts for 50% to 60% of all reconnaissance methods. With the exponential growth of the space reconnaissance system sensors and information volume, the information analysis process has become more and more strict, extracting accurate and reliable information from a large amount of information, and leaking useful information contained in the information. Doing so will be difficult and will require the application and support of information fusion technologies.

In terms of method, this paper mainly analyzes the start of the track, and then analyzes the error registration of the sensor. The sensor mainly has time alignment and spatial error alignment. The wavelet transform threshold denoising and Kalman filtering make the obtained information more complete. In the aspect of experiments, the experiments are mainly carried out on multiple types of spacecraft, after analyzing the observation accuracy of each sensor and eliminating the relative deviation, data fusion and processing are performed.

2. Method

2.1 Track Start
When the target is detected and the system track corresponding to the target is found, it is necessary to use the measurement information of the target to start the system track [4, 5]. Compared with other measuring equipments in the system, the GPS equipment has a slow data rate, but the reliability of the data is relatively large. Therefore, GPS information can be used well to start the system track. In addition, GPS information becomes more important when other measurement equipment is not working properly or the relevant target cannot be captured [6, 7]. Because the low data rate of GPS information cannot keep up with the frequency of system information guidance, at this time, it is necessary to interpolate the GPS information within the time interval of the two information.
However, due to the real-time nature of the information guidance, when interpolating, only the information at the previous time can be used, but not the information at the next time. Therefore, the method of GPS information interpolation is to perform extrapolation at the time of each information guidance Push [8].

2.2 Error Registration of Sensors
In the process of multi-sensor data fusion, it is necessary to first perform the spatiotemporal calibration of the measurement data of each sensor, also known as registration. For multi-sensor registration, its registration error mainly comes from the sensor system error [9]. Therefore, the first task to achieve multi-sensor-to-multi-target fusion tracking is to estimate and eliminate sensor system errors.

(1) Time alignment of the sensor
In the system, the measurement and control system has a uniform time period. Therefore, the time period of the information fusion system is based on the measurement and control system [10]. However, the information sent by each measurement device to the central computer is not necessarily obtained at the same time point. In order to ensure the accuracy of the fusion processing results; certain measures need to be taken to align the information in the same processing cycle to the same time point. For the asynchronous problem caused by the different sampling period of each sensor [11].

(2) Sensor spatial error registration
There are many methods to solve the problem of sensor spatial error registration. The classic ones are: real-time quality control method, least square method, exact maximum likelihood method, geocentric coordinate system registration method, Kalman filter method. These traditional multi-sensor registration algorithms are based on statistical model methods, which need to determine the source of the error and establish an accurate error model [12]. Due to changes in environmental conditions, the error model has also changed; especially with the continuous development of sensor technology, more and more sources of uncertainty error will appear, so these traditional methods can provide accurate alignment in process applications.

2.3 Wavelet Transform Threshold Denoising
The main idea of the threshold denoising method is that the data and the data after the wavelet transform have different characteristics, that is, the amplitude of the wavelet coefficient corresponding to the energy of the real data itself is large, and the amplitude of the wavelet coefficient of the interference noise is small. \( x \geq \lambda \), \( x \) represents the wavelet decomposition coefficient, and \( \lambda \) represents the set threshold.

By thresholding the wavelet decomposition coefficient \( \Omega_{j,k} \), the estimated wavelet coefficient \( \Omega_{j,k} \) is obtained, so that \( \Omega_{j,k} = \Omega_{j,k} \) is as small as possible, and the soft threshold function is selected as the threshold function:

\[
 f(x) = \begin{cases} 
 \text{sgn}(x)(|x| - \lambda), & |x| > \lambda \\
 0, & |x| \leq \lambda 
\end{cases}
\]

Where \( \text{sgn}(x) \) is a symbolic function. The selection of the threshold is a local adaptation threshold. The threshold of this paper is \( 3\alpha \). That is, the coefficients of the wavelet transform of each layer are arranged according to size, then the median is taken, and finally the median is divided by 0.539 to obtain the \( \alpha \) of the corresponding layer, \( x > 3\alpha \) is generated by the signal, and \( x \leq 3\alpha \) is generated by the noise.

2.4 Kalman Filtering
The core content of the Kalman filter is assuming that the value at time \( t \) needs to be predicted. According to its filter, the value that can appear at the previous time can be predicted by the optimal result:
$$Y(t | t-1) = AY(t-1 | t-1) + BU(t)$$  \hspace{1cm} (2)

Among them: $Y(t | t-1)$ represents the value that appears at the optimal result at the last moment; $Y(t-1)$ A and B are system parameters. When $Y(t | t-1)$ is updated, its trust has not been updated.

The trust update corresponding to the optimal estimate $Y(t | t)$ is:

$$T(t | t) = (1 - Kg(t)H)(t | t-1)$$  \hspace{1cm} (3)

3. Experiment

3.1 Purpose of the Experiment

Experiments are conducted on multiple types of space shuttles to explore the practical applications of multi-sensors for space reconnaissance data reception and fusion processing.

3.2 Experimental Design

The observation point (sensor) receives and sequentially records the electromagnetic waves reflected by the target, and records a series of discrete points formed by calculating the target's aerial position. For multi-sensor data fusion, detect targets in real time from given data, extract different targets from many given target information, perform data fusion analysis based on this information, and observe each sensor. Yes, it is important to perform data fusion and processing after analyzing accuracy and eliminating phase shifts. The data obtained in real time and the data stored in the database include observation data of multiple observation stations, and the data of one observation station may include multiple targets. Considering the influence of the differences in the duty cycle of each sensor, the inconsistent startup time, and the delay of the communication network, for the same target, there may be time differences in the data observed by each sensor. Perform time allocation before convergence, while synchronizing measurement information that is not synchronized with each sensor of the same target. The observed data shows the deviations of the target's longitude, latitude, radial velocity, latitude and target height. Therefore, it is necessary to calculate the spatial distance and interval between the traces of adjacent points on the data, and analyze the deviation between the sensors by comparing with the recorded value.

4. Discussion

4.1 Measurement data Preprocessing

Data preprocessing mainly includes coordinate transformation, field value elimination and data compression.

1) Coordinate transformation. For measurement equipment such as radar, infrared, and optics, target measurement is usually performed in their respective spatial polar coordinate systems, but the number of target measurement data is subsequently processed in a rectangular coordinate system, so it is sent to each measurement device. Before processing the input information, it must be converted into a unified radial coordinate system or earth center required by the test task. Therefore, the following coordinate transformations are needed first to process the measurement data:

1) Launch coordinate and geocentric coordinate system;
2) Measurement coordinate system and geocentric rectangular coordinate system;
3) Calculation of the position of the station in the launch coordinate system;
4) Measurement coordinate system and launch coordinate system;
5) Conversion of target angle information (azimuth angle, high and low angle) in different rectangular coordinate systems.

2) Field value culling. For field value points that appear in isolation, first, each component of the measurement value is determined by combining the statistical characteristics of the prediction residuals in the filtering, and the sampled data according to the determined conditions is used as the measurement data. Sampling data that do not meet the discrimination conditions are identified as
outliers, removed, and replaced with optimal predictions. For the spot-shaped outliers that appear in the film, the point-by-point outlier judgment method is used. When more than 10 consecutive outliers occur, the working state of this sensor is set to abnormal, and its qualification to participate in fusion is revoked. After judging that the subsequent measurement returns to normal, continue to use its measurement information.

(3) Data compression. The basic idea of multi-sensor data compression is to combine the points of multiple sensors on the same target at the same time, combine multiple detection data into one data, weight the measurement data of each sensor according to accuracy, and the combined point not only improves Precision, but also reduces the amount of calculation. In order to ensure real-time performance, the centralized multi-sensor fusion system needs to combine multi-sensor data into data similar to a single sensor for processing, which can reduce the system calculation amount and obtain the highest precision fusion data.

4.2 Sensor Analysis
Ground aircraft, electronic warfare or aeronautical siren and other aircraft use A1, A2, A3 and A4 respectively. Air reconnaissance system uses radar sensor SAR uses infrared sensor IR and optical sensor EO to identify the aircraft and obtain simulated data about target attributes. These attributes Determined by radio frequency RF, pulse width PW, IR and photoelectric. As shown in Table 1, MRF(.) And MPW(.) Are determined by the radar sensor SAR.

| Synthetic probability | A1 | A2 | A3 | A4 |
|-----------------------|----|----|----|----|
| MRF(.)                | 0.26 | 0.42 | 0.19 | 0.23 |
| MIR(.)                | 0.32 | 0.33 | 0.26 | 0.23 |
| MPW(.)                | 0.46 | 0.21 | 0.0 | 0.15 |
| MEO(.)                | 0.39 | 0.19 | 0.17 | 0 |

As shown in Figure 1, the basic probability of combining the two types of evidence by the above methods is MSAR(.), MSAR-IR(.), And MSAR-IR-EO(.). The basic probability assignment of sensor SAR target recognition, the basic probability of fusion of SAR and IR evidence, and the basic probability of fusion of three sensors, SAR, IR and EO. The basic probability distribution function was reduced to 0.02 by blending uncertainties. If a threshold value of 0.5 is selected using a decision method based on the basic probability distribution, the final policy result is A1, that is, the dominant aircraft in the target spacetime. It is found from the obtained data that after fusing the data of each sensor, the obtained data is more accurate than the judgment result of a single sensor. At the same time, the validity and reliability of filtering theory in multi-sensor information fusion of space reconnaissance are described.
5. Conclusion
In terms of methods, this paper mainly analyzes the start of the track, and then analyzes the error registration of the sensor. The sensor mainly has time alignment and spatial error registration. The wavelet transform threshold denoising and Kalman filtering make the obtained information more complete. In the aspect of experiments, the experiments are mainly carried out on multiple types of spacecraft, after analyzing the observation accuracy of each sensor and eliminating the relative deviation, data fusion and processing are performed. Preprocessing the data, the main preprocessing includes coordinate transformation, outlier elimination and data compression. This ground aircraft, electronic warfare or airborne early warning aircraft, other aircraft, four types of aircraft, and three types of sensors, radar sensor SAR, infrared sensor IR and photoelectric sensor EO were analyzed. Finally, it is concluded that the effectiveness and fault tolerance have been significantly improved after data fusion.

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