Dual- satellite integrated intelligent reconnaissance autonomous decision-making model

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Abstract. Aiming at aerospace remote sensing technology, this paper proposes a dual- satellite integrated intelligent reconnaissance decision-making model, and establishes a double- satellite system. One satellite is used for "general investigation" and one satellite is used for "detailed investigation". The target is carried out by general investigation load. Track identification provides guidance for detailed inspection loads, thereby improving the accuracy, real-time, flexibility and intelligence of space remote sensing. The focus is on three aspects: investigation model design, key algorithm research and semi-physical simulation verification. The reconnaissance model design completes the conceptual design and process demonstration of the model. The key algorithm research part completes the research of the fast detection based on deep learning and the key algorithm of load imaging strategy decision in the system. The satellite semi-physical simulation verification is carried out by constructing the semi-physical simulation verification system.

Space remote sensing acquires remote sensing images through satellite Earth observation, and plays an important role in resource monitoring and emergency rescue. To ensure the accuracy, real-time and flexibility of space remote sensing is one of the major problems in aerospace remote sensing. For example, first, most remote sensing satellites have weak processing capacity and low intelligence accuracy, and most images obtained by visible sensing satellites cannot generate effective remote sensing image products. Secondly, the real-time performance is poor. The remote sensing images is limited by the distribution of ground monitoring and control stations, data transmission capabilities, satellite orbit and other factors. It takes about one day to accept the delay from imaging to the ground station, which cannot meet the requirements of security in emergency situations. Thirdly, there is a lack of flexibility. Most remote sensing satellites in our country operate on a single satellite. They lack cooperation among satellites and autonomous decision-making on the satellite. For targets with strong mobility, only a predetermined time window can be used for detection, which easily leads to the lack of high-value information. The research on satellite models with on-board autonomous decision - making, intelligent processing and cooperative application capabilities can effectively improve the satellite's comprehensive observation capability, especially for completing observation missions with high timeliness requirements (such as dynamic tracking of maneuvering targets at sea) in complex environments.

At present, some foreign optical remote sensing satellites, such as the USA navy earth reconnaissance satellite—NEMO (Naval Earth Map Observer)[1] 、German small bi-spectral infrared detection satellite—BIRD(Bispectral Infrared Detection). The on-orbit target detection or identification function has been realized to a certain extent, and the observation results and target information can be directly transmitted to the user through the relay satellite in real time. However, there is still a certain gap between China and those of developed countries in on-orbit information processing capabilities of remote sensing satellites. In this paper, artificial intelligence technology is used to study on-board autonomous decision-making and target intelligent identification algorithms, and a hardware-in-the-loop simulation platform is developed to carry out experimental verification.

1 Dual satellite system design

1.1.Function design

(1) Detailed reconnaissance satellite with small field of view.

The satellite visible light remote sensing load has a high resolution and a small photographing width, and is equipped with a two-axis tripod pan. The satellite remote sensing load can carry out a certain angle swing, and can carry out high resolution continuous imaging detection on specific areas.

(2) General reconnaissance satellites carry out large-scale wide surveys.

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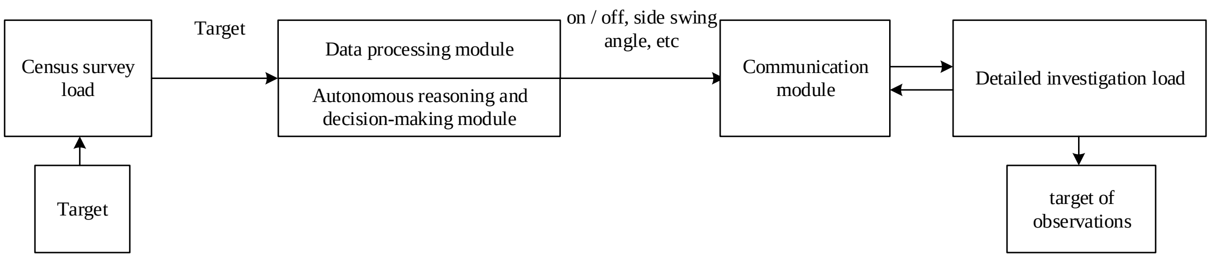

Figure 1. Operational process

The resolution of satellite visible light remote sensing load is low and the photographing width is large, so that the key targets in the field of view can be identified, the distance between the targets and the detailed reconnaissance satellite can be calculated, and the detection results can be transmitted to the detailed reconnaissance satellite through the inter-satellite link.

(3) Autonomous reasoning decision.

According to the position of the target and the state of the satellite, we can make an autonomous decision on whether to carry out observation or not, and provide information such as position, power on / off, angle for detailed reconnaissance satellite.

In the system, the general reconnaissance satellites and the detailed reconnaissance satellites have their own division of labor, which can greatly increase the time of satellite reconnaissance.

1.2. Model design

The model is mainly composed of general reconnaissance load, detailed reconnaissance load, data processing module, autonomous reasoning and decision-making module, and communication module. As shown in figure 1.

General reconnaissance load: orbit height 400 km, imaging width 100 km, resolution 10 m;

Detailed investigation load: the orbit height is 400 km, imaging width is 20km, the side swing angle is 45°, and the resolution is less than or equal to 1m;

Data processing module: light weight, low energy consumption, integrated and efficient on-board target recognition algorithm;

Autonomous reasoning and decision-making module: according to the identification of the target, independently formulate imaging strategies (on / off, side swing angle, etc.)

Communication module: to realize high-speed rate, low-latency communication and satellite-earth communication.

1.3. STK simulation demo

STK (satellite tool kit) is a satellite simulation kit developed by American Analytical Graphics Company. As a representative of space simulation software, STK has the characteristics of high degree of visualization and convenient use, so it has been widely and successfully applied at home and abroad. A certain scene is set up in STK, and the two-dimensional and three-dimensional simulation of satellite can be realized by setting parameters. The parameter settings are shown in table 1. Figure 2 shows the model in STK.

Table 1. Parameter settings

Parameter	general reconnaissance satellites	Detailed reconnaissance satellites
Track height	400 km	400 km
Orbital inclination	98	98
Longitude of ascending node	70	70
Eccentricity	0	0
Argument of perigee	0	0
Load width	100	20

The STK simulation shows that the observation time of double satellites is longer than that of single satellites. Under the guidance of the general satellite, the detailed satellite can start to observe the target by swinging sideways before the detailed satellite passes over the target, which can more than double the observation time.

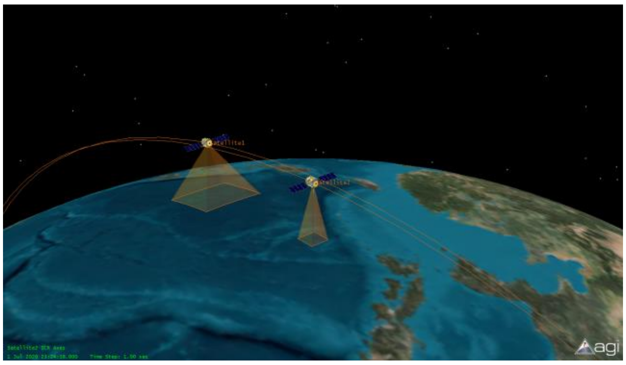

Figure 2. STK simulated picture

2 Research on key algorithms

The core of the on-board autonomous decision-making model includes two key algorithms: the on-board fast target detection algorithm and the on-board load autonomous decision-making algorithm.

2.1. On-board fast target detection algorithm

Target detection is the main task of satellite remote sensing. The goal of target detection is to identify interested targets from images and determine the specific position of targets.

2.1.1 Current status of related research

The traditional target detection method is usually designed by experts, so it has poor robustness and portability and it cannot meet the requirements of on-board rapid target detection.

With the development of machine learning, especially feature extraction and classification methods, major breakthroughs have been made in transforming the target detection problem into the classification problem of machine learning. The training process learns a classifier by monitoring, semi-monitoring or weak monitoring from the training data set. In the detection process, a series of region image blocks extracted by the sliding window algorithm are used as inputs of classifier, and predicted category labels are output (for example, whether the output of binary classification is a target or not). generally, the detection results need to be corrected and optimized through post-processing operations. The candidate region extraction algorithms include sliding window, superpixel segmentation, Edge box, SelectSearch, Bing, etc; Feature extraction algorithms include HOG, BoW, Texture features, Sparse representation features, Haar features and CNNs-based methods. The classifiers include SVM, AdaBoost, k-NearestNeighbor (KNN), conditional random field (CRF), sparse representation classification (SRC), artificial neural network (ANN), etc. Post - processing methods include NMS, Box - fusion, Bounding – box and other algorithms.

With the rise of deep learning, the accuracy of target detection continues to improve. In 2013[2], the neural network-based target detection method proposed by Szegedy can only reach 30 % mAP on VOC 2007 test set[3]. Subsequently, the mAP of R-CNN in VOC 2007 test increased to 48 %, and it increased to 66 % by modifying the network structure in 2014 [4]. R-CNN has made breakthrough progress in the field of target detection, followed by SPP-net[5],Fast R-CNN[6], Faster R-CNN[7],YOLO[8],SSD[9] and other algorithms. These innovative algorithms combine the field of traditional computer vision with deep learning and have achieved remarkable results. More and more scholars apply deep learning to target detection in remote sensing images [10-12].

The initial target detection algorithm used the sliding window method to extract regions. R-CNN used the SelectiveSearch algorithm to extract regions, then normalized the size of each extracted region, and then used CNN network to extract features. Finally, two full connection layers were connected behind the feature layer, and SVM classifier was used to identify the regions, and linear regression was used to fine-tune the position and size of the regions. R-CNN improved mAP directly to 66 % from about 30 % in VOC 2007. However, R-CNN has a large amount of computation and a slow processing speed, which is not suitable for on-board fast target detection.

2.1.2 Fast target detection based on yolo model

Based on the improved yolo target detection algorithm, end-to-end detection is realized, the position and category of the target are obtained in real time, the robustness of the model is improved, and the requirements of space remote sensing for fast, real-time and high accuracy are met.

Yolo is an integrated convolution network detection algorithm. The algorithm converts the detection problem into a regression problem. A single neural network is used to input the entire image into the network directly, and the position of the target bounding box and the target category are directly obtained through forward propagation only once, thus Yolo realized end-to-end real-time target detection.

Comparison of recognition efficiency between improved yolo algorithm and other on-board recognition algorithms;

Table 2. The comparison of algorithm recognition rate and speed

Model	Training set	mAP	FPS
SSD321	COCO	45.4	16
R-FCN	COCO	51.9	12
Improved Yolo	COCO	55.8	35

2.2 On-board load autonomous decision-making algorithm.

In order to obtain detailed information of satellite imaging time window and yaw angle, the position information of satellite and ground target should be described in the same spatial coordinate system, and then the spatial geometric relationship between satellite and ground target should be calculated.

Firstly, the space geometric coordinate system is established. The starting point of the satellite in the upper left corner of the platform is marked as (0, 0, H). The front and behind are in the x axis direction, and the left and right are in the y axis direction. The plane coordinate corresponds to the pixel coordinate of the image, and the height of the platform is in the z axis direction. The corresponding values of the satellite moving speed and its real moving speed are calculated through the scale, thus the x and y coordinate values of the movement are calculated, and the satellite spatial geometric coordinates are determined.

In the model, the reconnaissance satellite S_1 and the detailed reconnaissance satellite S_2 are designed to operate in the same orbit. Assuming that the coordinates of the reconnaissance satellite at this time are (X_0,Y_0,H), the spacing distance between the two satellites is D and the coordinates of the center of the field observed by the reconnaissance satellite are $(X_0,Y_0,0)$. In the reconnaissance field of view, the pixel positions of the target are determined, converted to the satellite orbit coordinate system, the coordinate information is transmitted to the detailed reconnaissance satellite, and then the angle information that the detailed reconnaissance satellite should adjust is calculated so that it can observe the target.

Figure 3 shows a schematic diagram of the reconnaissance satellite guiding the detailed reconnaissance satellite to adjust the angle to observe the target.

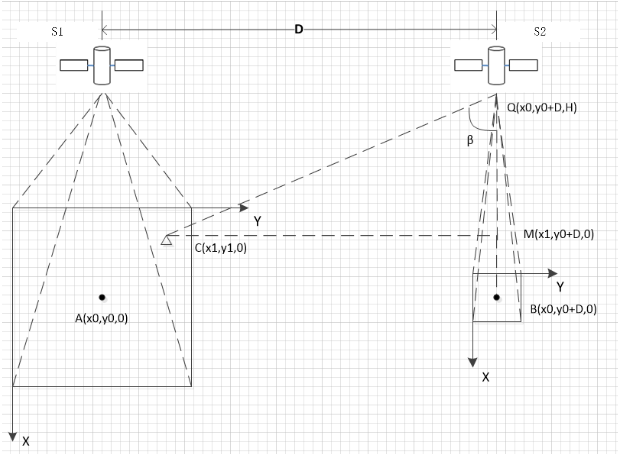

Figure 3. Geometric model

In the figure, A and B are the imaging points when S_1 and S_2 are vertically projected onto the ground. The projection center, C and Q are the target point and the detailed inspection satellite S_2 respectively. Q_1 is the point (X_1, Y_0+D, H), BM is the distance that the detailed inspection satellite S_2 swings in the field of vision in the x axis direction, and MC is the distance that S_2 swings in the field of vision in the y axis direction. α and β respectively represent the angle of oscillation of the satellite in the X and Y directions. Figure 4 is a schematic diagram of the calculation method of the detailed reconnaissance satellite angle adjustment:

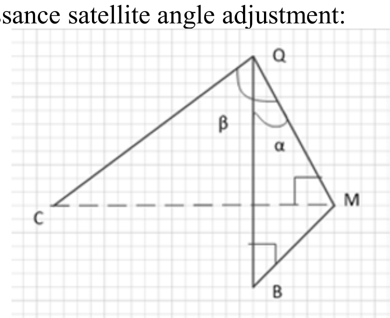

Figure 4. The calculation method of S2 adjustment angle

Angle calculation method:

$$\begin{cases} QM = \sqrt{QB^2 + BM^2} \\ \mathrm{Sin}\,\alpha = \dfrac{BM}{QM} \\ \alpha = arc\,\mathrm{Sin}\dfrac{BM}{QM} \end{cases} \quad (1)$$

$$\begin{cases} CQ_1 = \sqrt{MC^2 + MQ_1^2} \\ \mathrm{Sin}\,\beta = \dfrac{MC}{CQ_1} \\ \beta = arc\,\mathrm{Sin}\dfrac{MC}{CQ_1} \end{cases} \quad (2)$$

3 Hardware-in-the-loop simulation test

Satellite physical is expensive, and semi-physical simulation is one of the effective methods to verify the availability of key technologies. This chapter uses ground simulation to verify the model concept and key algorithms.

3.1 Demand analysis

The simulation model needs to meet the following requirements:

(1) satellite orbit simulation;
(2) ground environment simulation
(3) target detection
(4) autonomous decision – making

3.2 Model design

3.2.1 Hardware model design

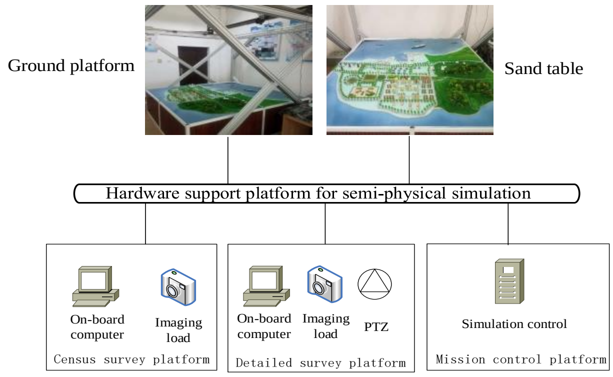

Figure 5. Hardware model design

The hardware model consists of a ground platform, a ground environment simulation experiment table, a general reconnaissance load platform, a detailed reconnaissance load platform, and a mission control platform. The model design is shown in figure 5.

PTZ on the ground: the 5-meter-long electric slide rail is used to stably control and adjust the translation speed of the camera. The height of the slide rail from the ground is 2m.

Sand table: the ground scene is arranged by sand table, including waters and ships.

The general reconnaissance load platform includes a microcomputer system and an imaging system. The imaging system adopts CMOS camera simulation.

3.2.2 Software system design

Basic support software includes Linux operating system, darknet, computer vision library OpenCV.

The basic data includes ship target data set, system data, algorithm configuration data, etc.

Support modules and components include load decision algorithm, target detection algorithm, I/O module, PTZ control, and network communication.

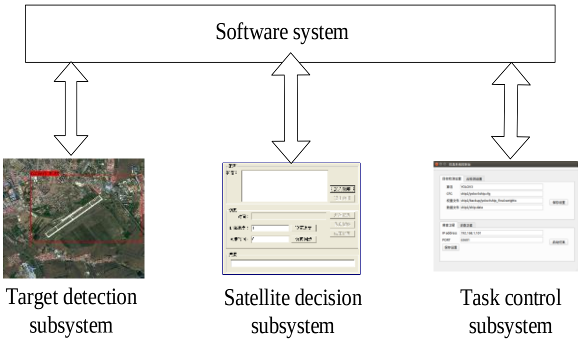

Figure 6. Software system design

3.3 Semi-physical simulation verification test

3.3.1 Simulation scene design

Figure 7. Sand table environment

The imaging process of sand table simulation ground and sea scenes is used to verify the capability of target detection, autonomous decision-making of load and cooperative autonomous decision-making process of dual- satellite model. The sand table environment is shown in figure 7, which includes the ground simulation environment, ocean simulation environment and randomly arranged targets. The detection target is a ship. The imaging width of the general reconnaissance satellites on the sand table is 1.2m, and the imaging width of the detailed reconnaissance is 0.6m. The verification process includes:

(1) General reconnaissance satellites target detection and verification. A fast target recognition algorithm is used for calculation. Providing target observation guidance for detailed reconnaissance satellites;

(2) Detailed reconnaissance satellite and self-determination of imaging strategy. Detailed reconnaissance satellites independently formulate and implement imaging strategies (imaging attitude angles) based on the target observation guidance information provided by the general reconnaissance satellites, combined with their own position information and payload imaging capabilities, to lock and continuously track targets.

3.3.2 Target detection model training

(1) The acquisition of data set

Download 1,500 images of ships on the internet, select 300 images randomly as test sets, rotate the remaining 1,200 images randomly by 45 degrees, zoom 15 - 25 %, cut and flipped vertically/ horizontally are used to expand the number of images to 4000 as training sets, and finally the target detection and labeling tool labellmg is used to manually label the test sets and targets existing in each image in the training set.

(2) Model training

The training set is used as input, and the improved Yolo model based on Darknet is trained. The model is initialized with weights trained on Pascal VOC data set. Epochs is 50 and Batch size is 64. GPU is NVIDIA Quadro M5000 and 8GB of video memory. After the model training is completed, the target detection accuracy on the test set is 95.7 %.

3.3.3 Simulation verification test

Through simulation experiments, the ability of target detection and load autonomous decision-making of the model is verified. Finally, the autonomous decision-making function of the model is verified.

Arranged ship targets randomly, general reconnaissance satellites load to obtain large field of view images, quickly detect target positions, transmit position information to the detailed reconnaissance satellite, and the detailed reconnaissance satellite adjusts the load imaging angle to capture and lock the target through an autonomous decision algorithm, and continuously track and observe the target.

Figure 8. General reconnaissance satellites find target

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Figure 9. Detailed reconnaissance satellite locks tracking target

4 Summary

The autonomous decision-making model of double-satellite integrated intelligent reconnaissance is of great significance and practical value in the field of satellite reconnaissance. The double satellite system increases the observation time of remote sensing satellites and improves the flexibility of the model. The improved on-board fast target detection algorithm meets the requirements of satellite fast, real-time and high-precision identification. This study trys to improve the status quo of China's space remote sensing, and provides a practical idea for the next development of China's remote sensing satellites based on the thought of artificial intelligence. The development of in-depth learning provides a new space for the progress of space remote sensing. In the new era of artificial intelligence development, space remote sensing will also progress accordingly.

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