

RESEARCH ARTICLE

SSC-KA: A Framework of Space Situational Knowledge Acquisition for Status-Cognition of Satellites

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ABSTRACT With the rapid development of space technology, the environment of the space domain has become more and more complex and changeable, which brought great difficulties in cognition of space domain activity. As space domain awareness (SDA) required, any relevant information and knowledge from various sources are needed as much as possible, while all of those can be sorted and integrated for effective cognition of space objects, including the cognition of their status. This paper proposes a knowledge integration framework (SSC-KA) designed for the cognition of space target and its status. In the framework (SSC-KA), open-source information and data acquired from multi-kinds of sensors are sent into parallel channels, and then processed by the algorithm this paper designed into sequence data as the channels' output. Furthermore, the rules and four statuses defined in this paper can be judged for the anomaly detection of satellites. Based on the space domain knowledge acquisition framework of SSC-KA, this paper describes a complete abnormal state detection method for satellites step by step through multi-level feature engineering. Therefore, the method is used to analyze four different statuses of satellites in this paper, to verify the validity and feasibility of the application of the method in the cognition of spatial events, thus laying the foundation for the cognition of Space Domain Awareness.

INDEX TERMS Space domain awareness (SDA), knowledge engineering, anomaly detection, activity cognition.

I. INTRODUCTION

During the last decades, the economic value of space assets continued accelerating by more than 10% [1] annually. The maximum investment transaction value has grown more than 300% since 2018 [2]. Space has become the highland of military, civil and commercial within the advantages of information acquisition and transmission. Years before most spacecraft or other assets owned by the governments or military organizations were large, expensive, and hard to repair. Until the first flight of a CubeSat in 2003, spacecraft were already getting smaller, the increasingly miniaturized electronics, commercialization and standardization of

traditionally bespoke satellite subsystem components, and access to launch vehicles as secondary payloads have also contributed to the improved accessibility of space and a large increase in satellites and satellite operators. Nowadays, commercial entities (Space X, One Web, Planet Labs) have already sent their giant constellation into the earth's orbit for space-based internet access. Reference [3], [4], [5], [6], [7] Since then space situational awareness has recently become an important research topic due to the enormous amount of space objects.

Space situational awareness (SSA) [8] is the perception of the elements in the environment within a volume of time and space, the (organizational) comprehension of their meaning, and the projection of their status shortly (in the space domain). SSA is the first step of space domain knowledge,

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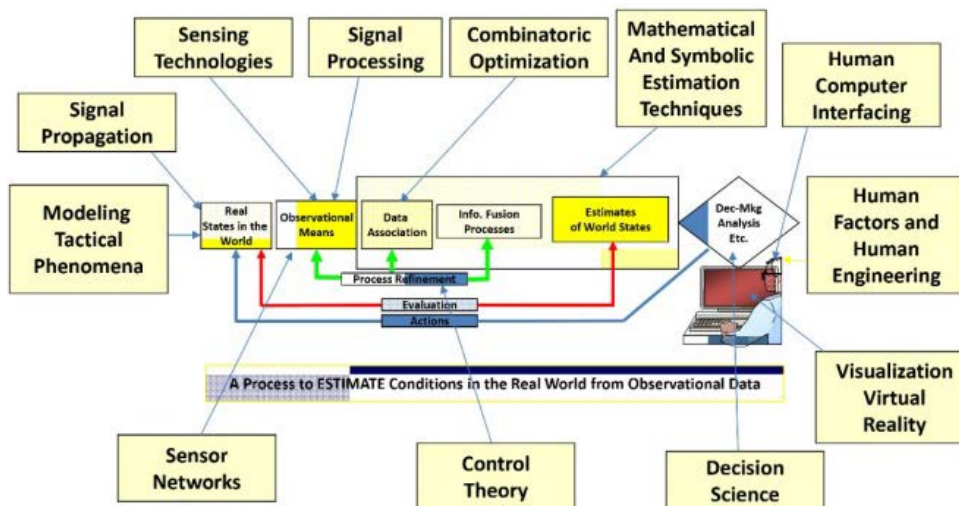


FIGURE 1. The whole process of multi-source information fusion.

followed by the concept of Space Domain Awareness (SDA). SDA simply elevates SSA to encompass all elements in the space environment as well as operators and human decision-makers and ground-based elements that affect space activity and cements the similarity of SDA with existing infrastructure and policies enabling air domain awareness [9] and maritime domain awareness [10]. Said differently, SDA is the actionable knowledge required to predict, avoid, deter, operate through, recover from, and attribute lead to the loss and/or degradation of space capabilities and services. The main purpose of SDA is to provide decision-making processes with a quantifiable and timely body of evidence of behavior(s) attributable to specific space threats and/or hazards. SDA encompasses all activities of information tasking, collection, fusion, exploitation, quantification, and extraction to end the incredible threat and hazard identification and prediction [11]

Until nowadays, SDA still lack credible scientific and technical rigor to quantify, assess, and predict space domain threats and hazards. Reference [25] the current state-of-the-art suffers from a number of inadequacies:

- No standard definitions of elements in the space domain;
- Descriptions of space objects and events are limited;
- No standard method of calibrating sensors and information sources has been developed;
- Tasking is addressed to individual sensors for specific data rather than to a comprehensive system for information required to address needs and requirements;
- No rigorous understanding of space environment effects and impacts on space objects;
- No framework that encourages and enables big data analysis, and supports an investigative ‘from data to discovery’ paradigm.

In general, we lack a consistent method to understand all of the causes and effects relating space objects and events.

Enabled by the most recent advancement in sensor technology, researchers and operational engineers rely on a large

amount of tracking data that can be processed to identify, characterize, and understand the intention of space objects [12]. Improving methods applied to the SDA domain task will require up-to-date approaches and algorithms that will be able to predict and prevent satellite anomalies.

In this paper, we aim at designing an effective framework for multi-source information on relevant space assets to provide a more accurate result for satellite Anomaly detection. Multi-source information fusion is a sophisticated estimation process that allows users to assess complex situations more accurately by effectively combining core evidence in the massive, diverse, and sometimes conflicting information received from multiple sources. It involves integrating information from these multiple sources to produce specific and comprehensive unified estimates about an entity, activity, or event. Multisource fusion systems seek to combine information from multiple sources and sensors in a wide variety of applications to achieve analysis and decision-supporting inferences that cannot be achieved with a single sensor or source. Designing and implementing data and information fusion systems requires a multidisciplinary approach, as seen in the diagram below that shows the disciplines and methods needed to achieve holistic system designs.

II. RELATED WORK

As for the SDA tasks, the information fusion method is still under research. With the rapid development of the theory and technology of AI, more and more difficult and complex SDA tasks can be solved now. Firstly, the machine learning technology offers emergent solutions to many industrial systems, such as transportation [13], manufacturing [14], video surveillance [15], climate change [16], and net-working [17]. Machine learning technology [18], [19] plays an important role in solving practical problems. The article [20] present an adaptive strategy of active control information updates for use in dynamic collaborative activity, which shows applicable

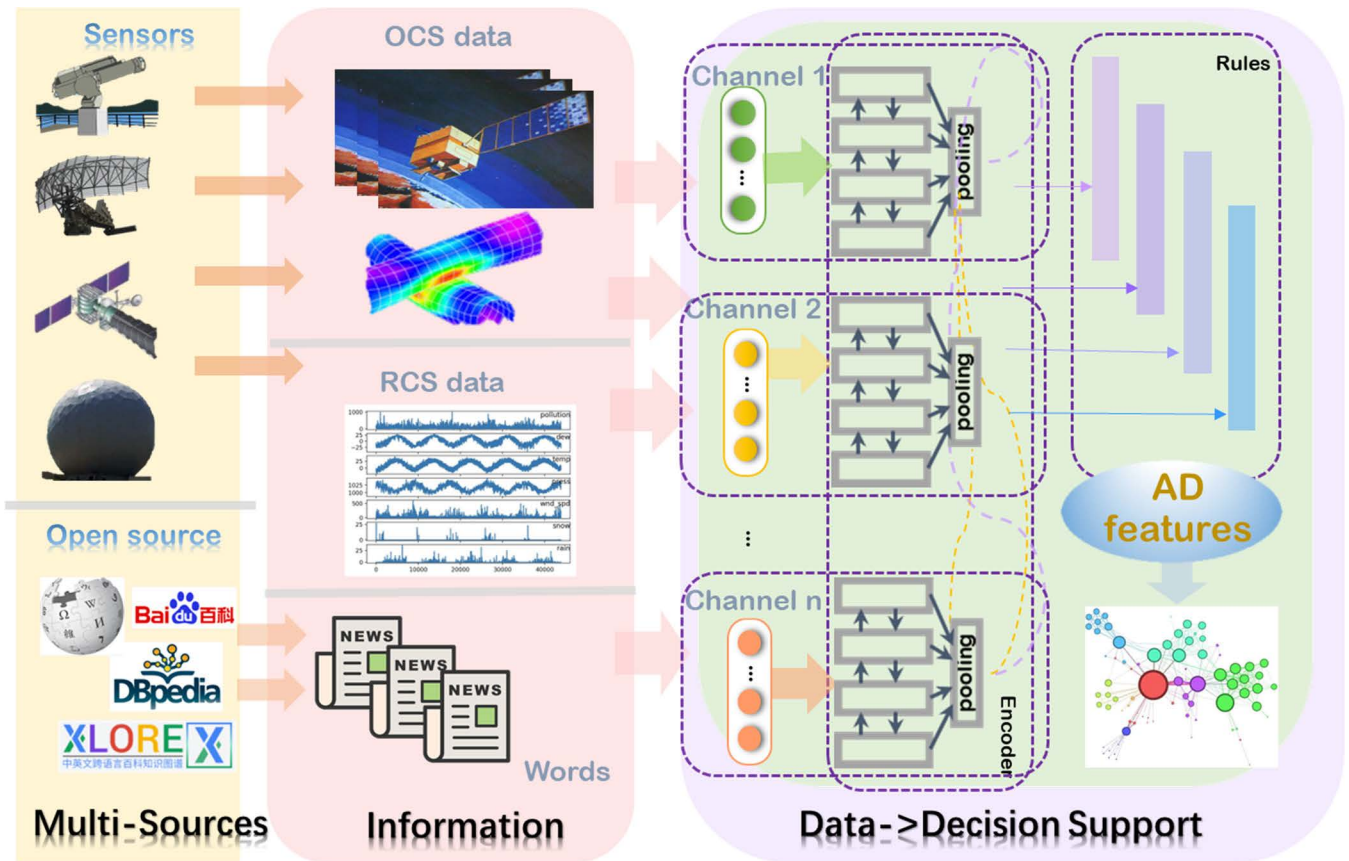


FIGURE 2. The whole process of multi-source information fusion.

ranking methods of semantic data mining for selecting relevant information in collaborative activity.

Especially for the situation awareness problem where the original analytical model is complex or it is difficult to obtain the real model, the machine learning algorithm helps to provide a solution to some extent. As to administrate the space domain assets, anomaly detection is the basic layer of the task. Previous work [21], [22], [23] had made the framework for TLE and special image source of information fusion to identify the abnormal status of satellites. In this work, we can make sure that the more kinds of characteristics for the satellite, the more accurate the detection results. To get the more effective SDA knowledge, we try to figure out a more conducive method to get more relative information for Anomaly detection.

The main purpose of this investigation is to design a framework for several sources of information fusion to diagnose whether the status of a satellite is abnormal. The framework is composed of multi-channel information process and made the fusion algorithm based on the attention mechanism for the structure data from every channel. The following section formalizes the framework and our approach.

III. THE FRAMEWORK OF SPACE SITUATION KNOWLEDGE ACQUISITION

In this paper, we propose a framework for Space Situation knowledge acquisition in order to integrate space situational resources from multiple sources more quickly, comprehensively and systematically for Space Situation Awareness activities and Space Domain Awareness activities. The framework of space situation knowledge acquisition (SSC-KA) is showed in figure 2. The framework consists of three main phases, which are multi-channel source information, pre-processing to generate data, and multi-channel to generate knowledge conclusions for decision supporting.

In the first stage, knowledge from various sources should all be obtained, which including open-source (news, report, websites, etc.) and sensors (optical sensors, ground-based radar sensors, and space-based sensors). In the second stage, the multi-source knowledge will be pre-processed separately for generating information that can be understood by the system. In the third stage, the information will be processed into structured data by several different channels with targeted models (encoder-decoder and other types of models) so that the data from each channel will be calculated based on rules. Finally, the data can be used for the space situation knowledge

representation by judging the status of space targets such as satellites.

The characteristic of the framework SSC-KA is that the information obtained from multi-sources with unique characteristics should be processed independently and respectively. Besides, the embedding layer to separate entity characteristic data from their respective space migration to a unified space, verify the repeated features and supplement effectively. Above these, the accuracy of space entity (like satellites) can be improved by the complementarity of multi-modes.

A. MULTI-SOURCE INFORMATION INPUT

The SSC-KA we proposed has considered several sources of information, which include open sources information and structured data from sensors.

Details are shown in table 1.

TABLE 1. The main source of input information in the SSC-KA framework.

Sources	Input Channel	Information Type
Space news	Open-source	Words
Reports, Essays, Patents, etc.	Open-source	Words
TLE data	Open-source	Structured data
OCS data	Sensors	Structured data
RCS data	Sensors	Structured data
Other Source	Image or the others ^a	Unstructured data

^a image data can be pretrained by CNN or other algorithms to be transformed into structured data which is not discussed in this study

a) Texts-Knowledge

The text-knowledge means the information from OSINT (such as news, reports, and other information in word or text form). We can get information from OSINT focusing on the prior information of satellites. In this data process channel, a lot of NLP (Natural language processing) methods can be used appropriately like GPT-3 and BERT.

b) TLE-Orbital Knowledge

Fundamentally, the underlying issue with SSA is that much is based only on a rules-based system with no information about relative confidence or estimation of how informative a TLE is. In addition, while orbit propagation is well understood and can be used to forecast a collision occasion in advance, estimate errors could lead to false alarms.

c) Photometric Knowledge

Photometric knowledge is an important information source for space target tracking, which plays an important role in satellite identification, anomaly detection, and pose estimation. Optical observation is passive observation, its detection ability is inversely proportional to the square of the distance, and the tracking accuracy is higher. The photometric knowledge has been acquired as fig 3 showed.

d) RCS-Knowledge

The radar cross-section (RCS) of the space target, which can usually be obtained by space surveillance ground-based

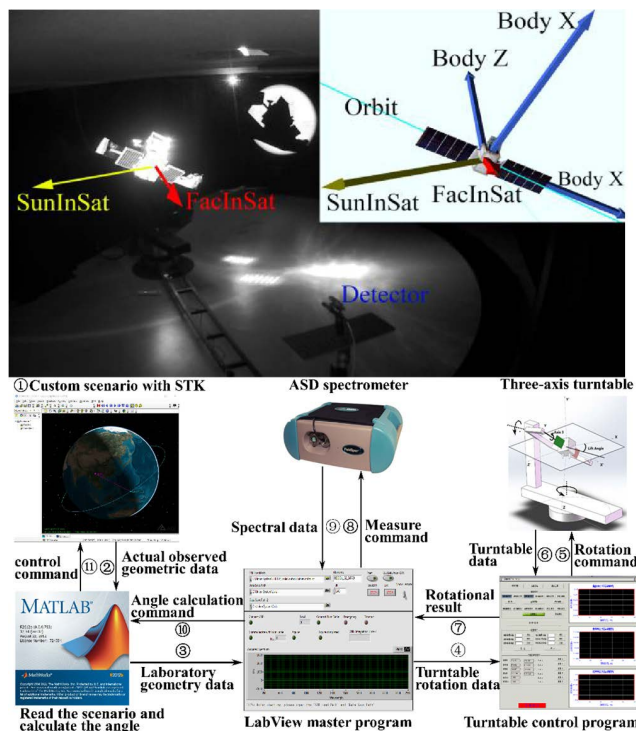


FIGURE 3. The scenarios and methods of the photometric knowledge have been acquired.

radar, is closely related to the target’s attitude motion, shape size, surface material, and other attributes. It is one of the key information sources for tracking and recognizing the space target. To fully exploit the attitude motion information in the RCS sequence of space target, the dynamic RCS observation sequence is studied. The major method of obtaining RCS data is shown in table 2.

From the perspectives of the attitude motion period inversion and the attitude motion pattern recognition, the inversion of the rotation period and precession period is studied, and the RCS feature extraction method for distinguishing the three-axis stable target from the unstable rotation target is explored.

TABLE 2. The major method of obtaining RCS data.

Method	Full name
GO	Geometrical Optics
PO	Physical Optics
GTD	Geometrical Theory of Diffraction
PTD	Physical Theory of Diffraction
UTD	Uniform Theory of Diffraction
MEC	Method of Equivalent Currents

B. DATA PROCESSING CHANNEL

As the SSC-KA framework showed, the multi-sources of information put into the system would be processed in parallel channels individually. Through the pretraining

process, the information has transformed into sequence-structure data set. Then for each channel, the sequence data can be processed independently and specifically. In the SSC-KA framework, the major three-channel is described as follows.

a) OCS-Data

For the processing of photometric data, traditional research focuses on obtaining the characteristic information of the target’s working state and structure by the inversion method. The main deficiency of the inversion method is that the observation data is interfered with by random noise, which makes it difficult to apply the theoretical analysis method to the inversion of the actual observation data, and the coupling of the target characteristic information and noise makes it difficult to obtain and analyze more detailed features of the target. In addition, signal coupling makes it difficult to obtain spatial target motion from target photometric data. In the photometric data process channel of SSC-KA, the data is transformed to OCS data for space target information by the algorithm as fig 4 showed.

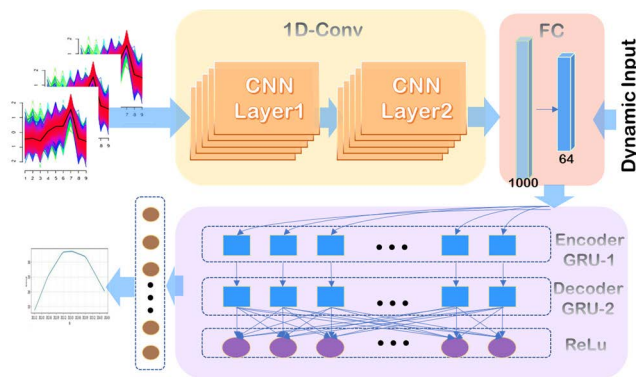


FIGURE 4. The process of OCS-data is transformed by the photometric image.

The optical cross-section (OCS) is widely used to represent scattering characteristics of space objects [24]. OCS is influenced by the geometrical shape, surface material, attitude of an object, and relative position of the sun-space object-observation station, but it is independent of the detection distance and the specific parameters of the detection system. According to the variation rule of the OCS, the inversion and identification of the attitude, geometry, and working state of space objects can be performed. In this paper, we take the OCS curves as experimental data.

In the OCS-Data Process, the OCS data will be transformed by the mode of fig 4. The model combined RNN and CNN to realize automatic feature extraction of satellite OCS curves. And the model consists of three parts: Encoder, Decoder and Classifier. The Encoder is mainly composed of 1D-CNN (1-dimensional convolution), which takes OCS sequence as input and generates feature vectors of fixed length. And the Encoder contains two 1-D convolution layers, where the

1-d convolution is defined as,

$$f_{conv}(s) = (\mathbf{W} * \mathbf{x}) [s] = \sum_{i=0}^n \mathbf{W}(s - i)\mathbf{x}(i) \quad (1)$$

where, x is the input sequence data, n is the length of sequence data, W and S respectively represent convolution kernel and sliding step number, and f_{conv} are the output vector after convolution.

In the Decoder, two GRU layers are used to reconstruct OCS curve. The Classifier consists of three full connection layers using ReLU activation functions and one output layer using sigmoid activation functions. The eigenvectors generated by the encoder are the inputs to the classifier. The output layer uses the sigmoid function to map features to categories.

b) RCS-Data

In the RCS data process channel, deep learning is used to detect the abnormal posture motion pattern of the space target in the RCS sequence. Gated Recurrent Unit (GRU) network model was first proposed in 2014, which is the improved version of the LSTM network. GRU consists of two gates making the structure simpler and clearer, while the training speed can be improved. The improved GRU neural network, as a traditional recurrent neural network, has good performance in the recognition, detection, and prediction of time series data, and can be used to extract the deep essential features of RCS sequences.

In this channel, the abnormal detection method for spatial target RCS based on Gated Recurrent Unit (GRU) deep Recurrent neural network is shown in fig 5.

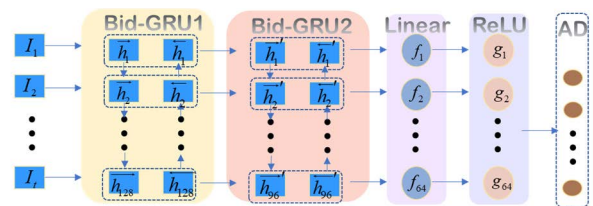


FIGURE 5. The process of RCS data transformed from radar data.

Here the model (as Figure 5 showed) for the RCS-Data processing channel constructed in this paper consists of an input layer, four hidden layers and an output layer. The hidden layer is divided into GRU hidden layer and full connection layer. The number of nodes in the input layer is equal to the sample input dimension. Moreover, the Bidirectional Gated Recurrent Unit (bi-GRU) can be adopted by the model in GRU hidden layer to learn the complete before and after information of time series for higher accuracy. And the ReLU function between the feature output layer and the feature output layer makes the feature extracted in network training more effective.

c) TLE Data

As the TLE information (as fig 6 showed) was acquired from open source, the structural data already contains the

motion characteristic. But still, the TLE data should be pre-trained for integrated orbital status identification.

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AAAAAAAAAAAAAAAAAAAAA
1 NNNNNU NNNNAAA NNNNN.NNNNNNNN +.NNNNNNNN +NNNNN-N +NNNNN-N N NNNNN
2 NNNNN NNN.NNNN NNN.NNNN NNNNNNNN NNN.NNNN NNN.NNNN NN.NNNNNNNNNNNNN
    
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FIGURE 6. The standard format of TLE data.

In this channel, the TLE data will be processed into the orbital elements' tensor data.

C. FUSION WITH ATTENTION MECHANISM

The attention mechanism is often used for training neural networks, which allows models to learn alignments between different modalities. In this paper, the self-attention mechanism is adopted to further capture the sensor-source dependence between sequences in sensor data samples.

The different sources of satellites' information will form the different characteristics of several features. H^O, H^R, H^T as the eigenvector of the sequence data through parallel processes can be calculated. Each line H^O, H^R, H^T is denoted as and the query, key, and value matrix are generated as followed.

$$Q^O = W^Q * X' \tag{2}$$

$$K^O = W^K * X' \tag{3}$$

$$V^O = W^V * X' \tag{4}$$

$$Z^O = \text{soft max}(\frac{Q^O(K^O)^T}{\sqrt{d_K}})V^O \tag{5}$$

d_K is the dimension of the key K^O .

Here the multi-attention mechanism is adopted with the Q^O corresponding lines and K^O, V^O are mapped to different subspaces after linear transformation of different parameters. Besides, self-attention operation is independently performed in each subspace. The final representation Z^O is obtained after splitting. The attention mechanism algorithm is shown in fig 7. All the information from open source and RCS data can supplement the motion character of satellites, and the information from OCS can form the attitude features. Data through different channels will be used to anormal detection after the attention fusion procedure.

D. STATUS OF SATELLITES

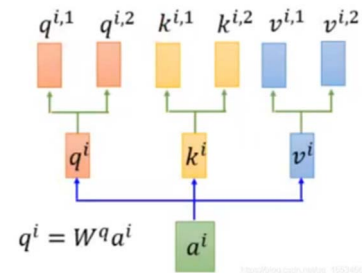
Here we define the satellite node as below (Model of Satellite: S),

$$S = (S_{motion}, S_{gesture})$$

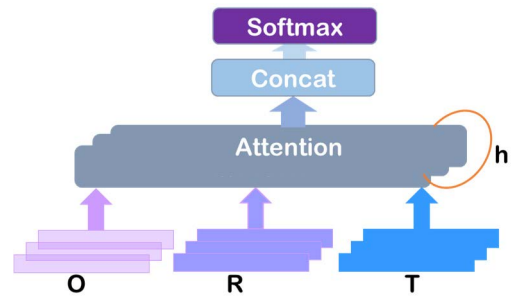
$$\begin{cases} S_{motion} = (o_{t1}, o_{t2}, \dots, o_{tn}) \\ S_{gesture} = (q_{t1}, q_{t2}, \dots, q_{tn}) \end{cases} \tag{6}$$

where each raw satellite motion characteristic S_{motion} is a sequence of the orbit features of the satellite and $S_{attitude}$ is a sequence of the attitude status of the satellite.

Since the data through the process above, the final task of SSC-KA is to classify the status of satellites into four broad



a) Coefficient design in attentional mechanisms



b) Attention mechanism based on three channels O-R-T

FIGURE 7. The Data fusion procedure with attention mechanism.

categories A_1, A_2, A_3, A_4 . The data processed will keep as the input for anomaly detection and go through the rules we've come up with a lot of experts' experience. As fig 8 showed.

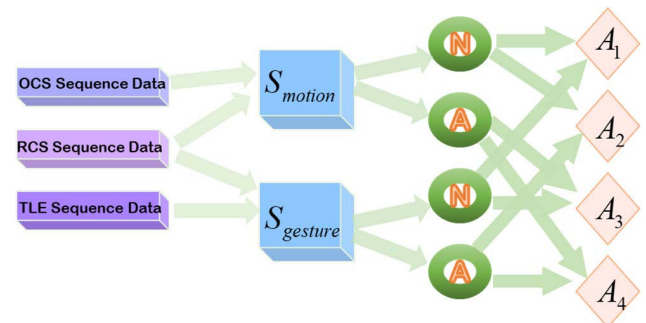


FIGURE 8. The Anomaly Detection of the four statuses about satellites.

We describe the satellite status comprehensively by its attitude and orbital motion as table 3 shown.

TABLE 3. The description of four states.

Status	Motion	Attitude	THE BEHAVIOR OF THE SATELLITE
A_1	normal	normal	The Normal Operation
A_2	normal	abnormal	Under Working Mode
A_3	abnormal	normal	Orbital Maneuver
A_4	abnormal	abnormal	Mechanical Malfunction Special Emergent Operation

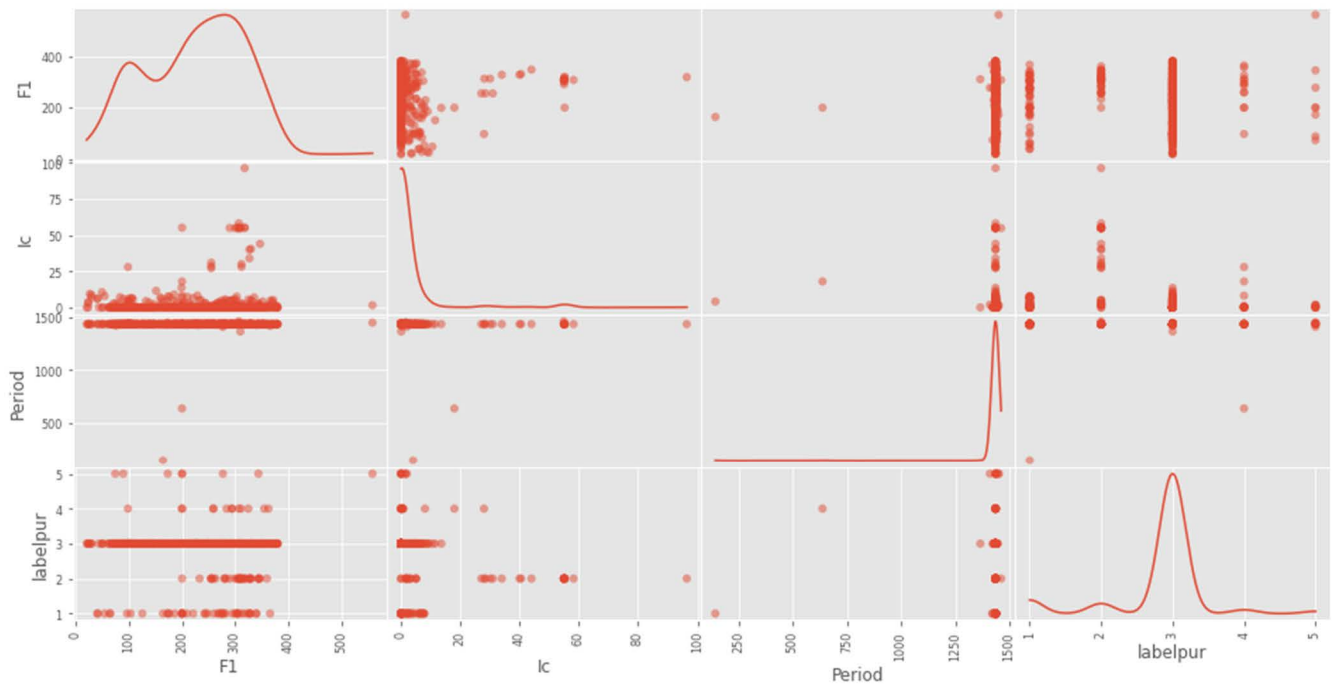


FIGURE 9. Connections between Different Motion Elements of the Targets in GEO Belt.

In the first mode, there are no abnormal phenomena in the motion state and attitude of the satellite, so it is judged to be a normal operation state. In the second mode, the motion trajectory of the satellite does not appear abnormal, that is, the satellite maintains its normal orbit along the originally planned orbit, but its attitude changes. It is judged that the satellite adjusts its attitude for specific work or activities, which is one of the working modes. In the third mode, the satellite's orbital motion state appears abnormal, that is, different from the orbit maintenance state it has most of the time, and the orbital elements appear abnormal, while the attitude has not yet appeared abnormal, and it is judged to be an orbital maneuver state. In the fourth mode, the satellite's orbital motion state is different from its original orbit maintenance state, and the satellite's attitude also appears abnormal, which is divided into two cases, one is that the satellite has a mechanical failure that causes problems in its orbit and attitude control, and the other is that it consumes fuel to make orbit and attitude changes to achieve important operations or behaviors.

IV. EXPERIMENTS AND RESULTS

In this section, we demonstrate the validity of the framework and method by applying the acquired satellite-related data to the proposed framework and method in this paper. All the experiments are implemented based on PyTorch.

A. TLE PRETRAINING PROCESS

We can obtain the TLE information related to spatial targets by knowledge acquisition from open source. In this section,

the information from the UCS space target database on January 1st, 2022 will be sent into the TLE DATA PROCESS CHANNEL.

From the database we can get the information of satellites with 29 characters. Moreover, there are some characters are words or sentences. And we choose the information of the GEO belt satellites to pretraining channel. With supervised learning algorithm for feature engineering through manual feature annotation and labeling, the results are showed in Figures 9, 10.

It can be seen from the distribution attributes of different features of different GEO satellites in Figure 9 that some features are basically general. Therefore, we can initially believe that not every feature attribute of a satellite has important feature significance. However, due to the system's need for computing power and speed, we consider feature dimension reduction. The input satellite attribute information is quantified and reduced to low-dimensional data for satellite feature representation.

From the importance rank of the features (Fig 10) from open-source orbital information acquired, the satellites' motion information can be calculated by the attention mechanism above the original features, which can make the motion information of the targets in GEO belt embedding into two-dimensional space for characterization, as shown in Figure 11.

Since then we can see that the input information is complex and various types with about 29-dimension attributes. The pre-processing channel can effectively retain the important information obtained from open source channels and form

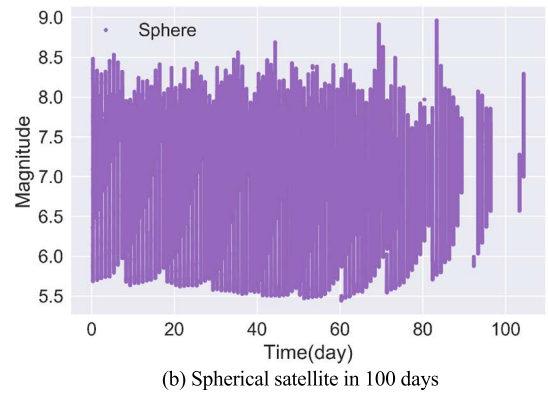
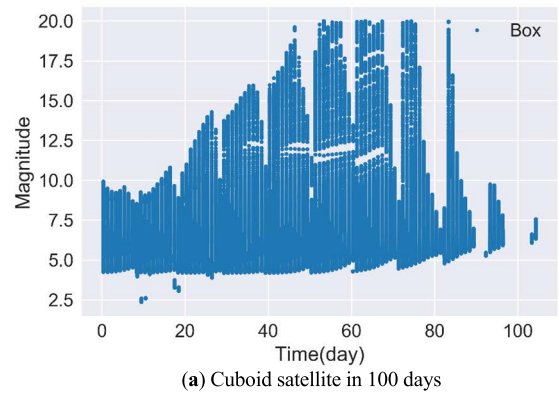
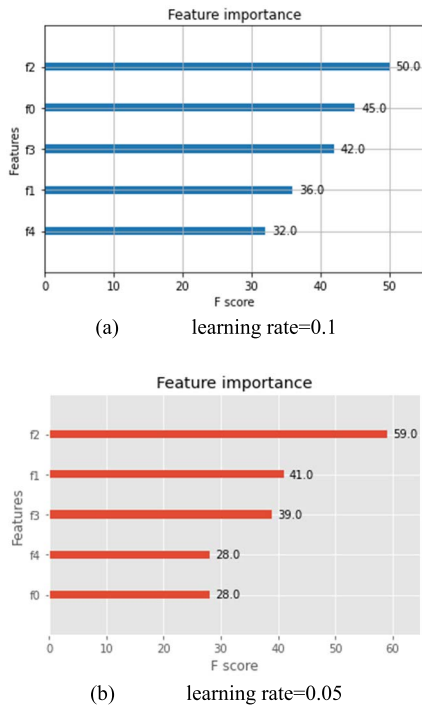


FIGURE 10. The TLE data has been computed by XGBoost model with the parameters set as, $max_dept = 4$, $n_estimators = 20$, $subsample = 0.7$, $colsample_bytree = 0.7$. Besides, the different learning rates can make the different prediction effects as (a) and (b). Both the figures showed the importance value of the different features, of which can be seen that the second feature is the most influence characteristic which should take the most weight on the attention mechanism.

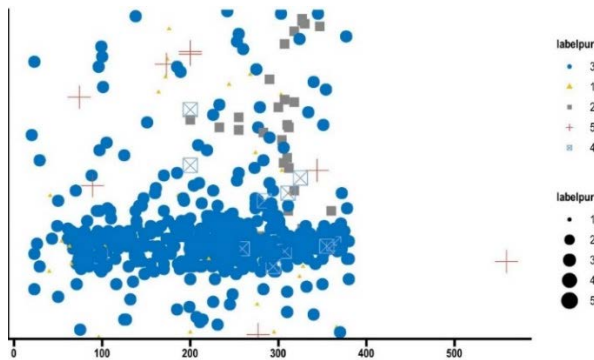


FIGURE 11. The two-dimensional presentation for the objects in the GEO belt.

low-dimensional data representation, which can effectively reduce the cost of computing and storage while preserving all kinds of important satellite information.

B. OCS-DATA PRETRAINING PROCESS

In the photometric data processing channel, the laboratory test data can be used for sampling the object’s photometric value as shown in fig 12. Here we accelerated the photometric data of the two different shape objects in 100 days, and take the sequence data into the processing channel. Figures (a) and (b) show the photometric curves of the cuboid

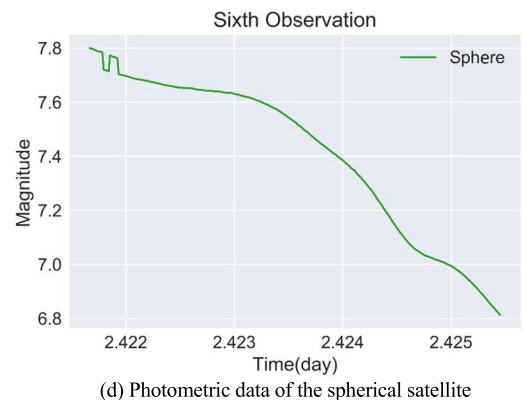
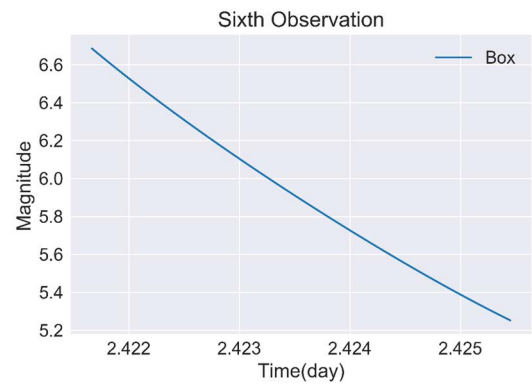


FIGURE 12. The Photometric curves of the different shapes of space objects.

satellite model and spherical satellite model within 100 days. Figures (c) and (d) show the photometric curves of cuboid objects and spherical objects in the sixth observation batch.

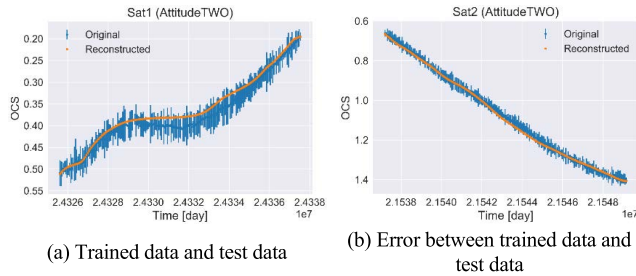


FIGURE 13. The comparison between trained data and test data.

Then we use the model in section 2.B and fig 4 showed, that the photometric data in a certain interval can be acquired and trained. Here for demonstration, the 1400 groups of data have been trained for the OCS-processing model, and the result for the comparison of laboratory simulation measurement data and real measurement data are shown in fig.13. From the results, the validity of the model and algorithm in the photometric data process channel has been showing.

C. RCS-DATA PRETRAINING PROCESS

In the RCS-data processing channel, the satellite (as the model of fig 14 showed), and the information of the experiment we designed is shown in table 4.

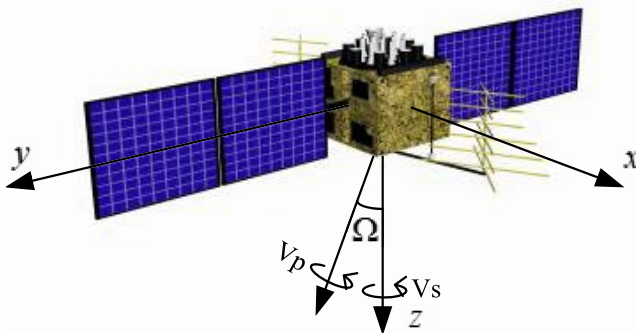


FIGURE 14. The Space target simulation model. The satellite spins from main-axis, Z-axis, and V_p is the spin rate, V_s as the precession rate, and the nutation angle.

TABLE 4. The experiment parameter.

Satellite (orbital elements)	Abbreviations	Value
Semi-major axis	a	7378.14km
Eccentricity	e	0
Inclination	i	98°
Argument of periapsis	ω	120°
Longitude of ascending node	Ω	110°
True anomaly	φ	0°

The loss function and accuracy curve of GRU deep neural network model after 100 iterations are shown in Figure 15.

TABLE 5. The anomaly type of the attitude changing mode.

Type	Anomaly Situation					
V_p (revs/min)	1	1	1	3	3	3
V_s (revs/min)	3	3	5	3	5	5
Ω (°)	10	20	10	10	10	20

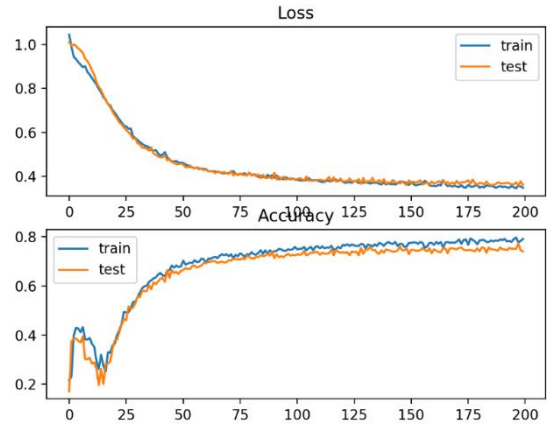


FIGURE 15. The model loss function curve and model accuracy curve.

It can be seen that the loss function of the training set and verification set basically remains unchanged and converges to 0 after more than 40 training rounds, and the accuracy curve converges to 1, proving that the GRU deep neural network model constructed has no under-fitting or over-fitting phenomenon, achieving good training effects.

D. STATUS COGNITION OF SATELLITES

In this section, we collected the multi-source of information from 29 Mar 2022 04:00:00.000 UTCG to 30 Mar 2022 04:00:00.000 UTCG, among which is a station (40.0386 N, 105.597 E). In order to analyze the effect of the method we proposed, we take the measurements as input to decide the status of space objects.

The experiment set as the table 6 shown as the satellites' motion mode discription, and the attitude mode set as the fig16 showed. In this section, the normal attitude mode we set is the normal attitude to ground triaxial stability. And the abnormal attitude set in this experiment as 45 degrees clockwise deflection along the body axis Y axis. The yellow axis represents the abnormal posture after rotation as fig 16 showed.

According to the definition in section 2, the four situations A1, A2, A3, A4 are the different states of satellites. The four states as the result of the satellites' anomaly detection can be figured out through the method we proposed in this paper.

In order to facilitate the analysis of the influence of satellite attitude and orbit anomaly on OCS observation results only, cubic satellite with different surface materials are used as simulation objects, and OCS simulation of four different working states is conducted respectively, as shown in the figure 17 below.

TABLE 6. Satellites’ motion mode.

Scene	Parameter	Ab	Value
Motion-1	semi major axis	a	42165.474245km
	eccentricity	e	0.000000
	inclination	i	0.141deg
	argument of periapsis	ω	103.684deg
	longitude of ascending node	Ω	0.000deg
	true anomaly	φ	204.472deg
	Motion-2	semi major axis	a
eccentricity		e	0.298798
inclination		i	0.141
argument of periapsis		ω	103.684deg
longitude of ascending node		Ω	24.472deg
true anomaly		φ	180.000deg

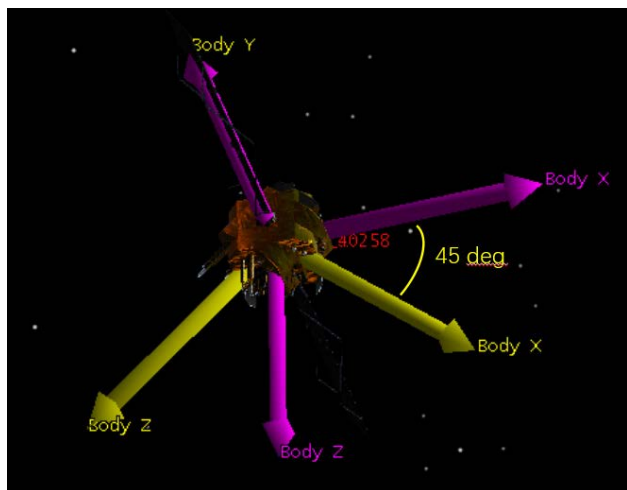


FIGURE 16. The model of attitude status simulation.

Therefore, we can generate characteristic curves for individual satellites through the SSC-KA framework (with both TLE data from open-source and sensor information acquired). By analyzing the characteristics of different situations, we can get different judgments about satellite states. From the Figure 17, the status of satellites can be seen. Here we summarize the results in the figure into a table, as shown in the table 7.

As can be seen from Figures (a) and (b) and (c) and (d), the peak phase of the characteristic curve is basically unchanged when only the satellite attitude is different, but its amplitude and number of peak values will change. The reason is that the satellite attitude changes, leading to changes in the position of the sun and the station in the satellite’s ontological coordinate system. For the satellite, its solar irradiation surface and reflection surface have changed. Due to the different optical materials on different surfaces, the satellite optical

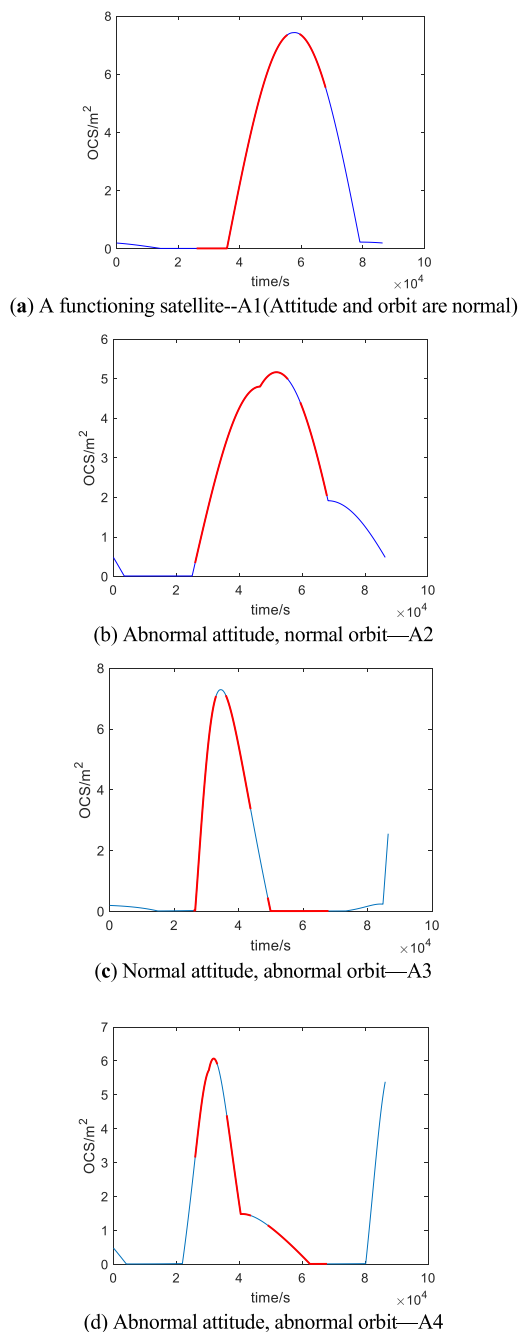


FIGURE 17. The Results about the Status Cognition of Satellites by SSC-KA.

characteristics detected by the station are also different. By figure (a) and (c) and figure (b) and (d) shows that only when the abnormal changes in orbit, abnormal satellite and station, the relative position of the relationship between lead to extreme value point of the phase change, at the same time, the relative position of the sun, satellite and station, can also lead to illuminate and the reflection surface, which embodied in OCS curve variation of amplitude. When both attitude and orbit are abnormal, the variation on the reflection curve is the synthesis of the two effects. Therefore, it can be verified that

TABLE 7. The status cognition results of four kinds.

Parabolic curvature $An=v^2/p$	Parabolic focus dot $p/2$	Status	THE BEHAVIOR OF THE SATELLITE
$\Delta An < 3$	$\Delta p < \sigma$	A_1	The Normal Operation
$\Delta An > 3$	$\Delta p < \sigma$	A_2	Under Working Mode
$\Delta An < 3$	$\Delta p > \sigma$	A_3	Orbital Maneuver
$\Delta An > 3$	$\Delta p < \sigma$	A_4	Mechanical Malfunction Special Emergent Operation

the state recognition and cognition of space objects such as satellites can be realized through the framework proposed in this paper.

V. DISCUSSION AND CONCLUSION

In the traditional research, an independent feature or one single channel of space target(or satellites) has been studied relatively mature for the target anomaly detection. This paper designs a knowledge integration framework (SSC-KA) and a method designed for the cognition of satellite status. Both the open-source information and the data acquired from sensors and other equipment can be sent into the SSC-KA framework for satellites anomaly detection of the four statuses. Besides, the four rules and statuses defined in this paper can be judged for the anomaly detection of satellites. The experimental results show that the TLE data and OCS data and RCS data can be divided into the parallel channel and processed independently. Since the results that came from each channel can get the accuracy value of more than 90%, then the results can be integrated for satellite anomaly detection. The experiments show the validity of the framework and the knowledge integration method this paper proposed.

However, the anomaly detection of satellites is the first step of SDA. There are a lot of challenges to the cognition of space domain objects. This article is written for the future space domain awareness technology by firstly making it clear to the cognitive framework of the space situational knowledge acquisition and designing an algorithm for multi-status analysis. While the space domain awareness still needs a lot to over-come for its multi-scale and hierarchical peculiarity. The follow-up study will continue to explore the effective approach for further deepen situational understanding and cognition.

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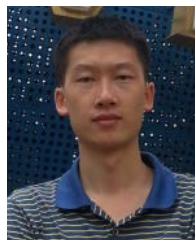


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