SCT2G: Model for Fast Satellite Activity Recognition in SDA

YINING SONG¹, ZHI LI², AND ZHANYUE ZHANG³

¹Graduate School, Space Engineering University, Beijing 101416, China
²Space Engineering University, Beijing 101416, China
³Space Safety Center, Space Engineering University, Beijing 101416, China
Corresponding author: Yining Song (yolandarabbit@163.com)

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ABSTRACT With the rapid development of space technology, the space domain environment has become increasingly complex and variable, which has created more challenges for space domain awareness. By classifying the problems faced by SDA, the overall idea of solving these problems by detecting points of variation is clarified. In this paper, a change-point detection method is constructed for space target data streams based on the T2G model, and the method’s effectiveness and performance are verified by simulating satellite data streams. This proves that the method proposed in this paper can quickly and effectively detect the change points of a civilian space target. Furthermore, we include a preliminary analysis of space target behaviour by analysing the calculated anomaly score. After verifying the method, we demonstrate its applications in several important fields (such as regular LEO satellites, LEO satellites with frequent orbit manoeuvres, and GEO satellites), which not only verifies the proposed method’s effectiveness but also yields much more space information. This can provide valuable evidence, recommendations and references for subsequent space situation analysis and space mission planning.

INDEX TERMS Cognition, space domain awareness (SDA), space target, sequential data processing.

I. INTRODUCTION

The concept of space situational awareness (SSA) [1], [2], [3], [4], [5] was first presented in a March 1998 research article. Since then, it has become the basis of space power, playing an important role in acquiring space superiority and acting as a key factor in realising space control. Subsequently, the contents and scope of SSA have been continuously enriched, while its implications have become more mature. SSA has not only been strongly linked to threats and hazards but has also provided opportunities to mitigate or reduce hazards. The construction of SSA equipment and its capabilities soon gained much attention around the world. While SSA involves the knowledge and characterisation of space objects and their operational environment, the term “space domain awareness” (SDA) [6] has been considered as an expansion of SSA that encompasses all elements in the space environment, as well as operators, human decision-makers and ground-based elements that affect spatial activities. In addition, SDA involves the knowledge required to predict, avoid, deter, operate through, recover from, and attribute causes to the loss and degradation of spatial capabilities and services. To provide decision-making processes that are quantifiable and quickly attributable to specific space threats or hazards, SDA encompasses all activities of information tasking, collection, fusion, exploitation, quantification, and extraction to aid in credible threat and hazard identification and prediction.

In addition, with the rapid development of space science and technology in recent years, human activities in space have been considerably upgraded, and space activities have become involved in various fields of national economics and people’s livelihoods. As an increasing number of activities and purposes can be accomplished in the space field and exploration continues in deep space, man-made objects have proliferated in space, including spacecraft, rocket stages, missile fragments, space debris, etc. Therefore, we need to propose new methods for SDA technology development; such methods once relied on sensor capability (such as the sensitivity and resolution of a telescope) [7], [8], [9], [10],...
To precisely determine the orbits of satellites, the traditional method is to employ astrophysics and orbital dynamics [14], [15], [16], [17]. However, the theoretical difficulty of this method is relatively high, and its application in engineering will need to account for the model complexity brought by the management of large space targets in the future. With the explosive growth in the number of space targets and the increasingly complicated actions of satellites, the technology for SDA needs to be constantly upgraded to meet current requirements.

In our research, we design a fast calculation process for satellite-orbit data pretraining, which can determine abnormal targets in real time for large-scale data, as shown in Fig. 1. This process can be followed by using the sensor data to verify the real activity that the targets might be involved in, which compose the whole target activity cognition roadmap. Therefore, to meet the requirements of real-time information processing and mass data management of SDA, a new algorithm is provided in this paper for change-point detection of space target data after analysing the data of space targets in orbit to discover and judge abnormal situations of space targets with real-time speed, high accuracy and low computing power. This method can greatly improve the overall situational awareness capability with small cost in terms of improvements to the sensors, storage capacity and computing capacity, and it shows excellent performance and substantial application value.

II. PROBLEM AND RELATED WORK

To solve practical problems while shortening the reaction time of the observe, orient, decide, act (OODA) chain in SDA, we focus on using calculated satellite data in determining abnormal activities and states of satellites quickly, easily and lightly.

We acquired orbital data on January 1, 2022 and transformed the original data as follows:

\[ \{x, y, z, H = \sqrt{vx^2 + vy^2 + vz^2}\} \]  

From the 4-dimensional feature, we obtained a characteristic representation of the positions of the satellites, as displayed in Fig. 2 below (2-a is the first 2-dimensional feature, and 2-b is the second 2-dimensional feature).
From the distribution of the orbit data on January 1, 2022, shown in the figures, no obvious scattering or clusters are available to determine similar orbits of the satellites for calculation. It is also difficult to use this data for the transverse analysis of targets in orbit because the functions and design targets of satellites in low, high and medium orbits are very different. In this paper, we assume that the satellites’ orbit evolutions are independent and uncorrelated, which means that the satellites can be independently analysed to determine their operation states. Therefore, we independently analyse the longitudinal extractions of the historical data of in-orbit targets. From the independent time-series data stream of a single satellite, the behaviour pattern can be trained through a historical database with the data-driven model to analyse the existing state. For a single satellite, we can acquire time-series orbital data from the sensor device through a time-series model that captures the representative patterns underpinning the observed data. The orbit activities of space targets are usually divided into three categories: normal orbit operation $A_1$, orbit maintenance $A_2$ and orbit manoeuvre $A_3$.

In the case of normal orbit operation, the trajectory characteristics are smooth, and the time series data are not abnormal. In the case of orbit maintenance activity, the orbit timing data have a change point, but the orbit maintenance activities are basically constant; that is, the changes in the orbit characteristics due to each orbit maintenance activity are similar, and the change values are not very large. In the case of orbital manoeuvre activity, the difference is quite obvious. Because of its great flexibility, more extreme dynamics and high salience, orbital manoeuvre activity consumes more fuel, the variation in orbital characteristics is large, and the changes are much more frequent.

Therefore, to recognise these types of activities, we can use the following three methods:

### A. FEATURE-BASED MODELS

Recently, feature-based algorithms have become very popular and clear for intelligent calculations. Here, we select several popular feature-based algorithms for our method: logistic regression, AdaBoost, GBDT, XGBoost, and LightGBM. These algorithms capture various state representations.

### B. FOREST MODELS

The isolation forest algorithm was proposed by Zhihua Zhou’s team in 2008. In contrast to k-means, DBSCAN and other algorithms, it does not use indicators such as distance and density to describe the difference between samples but directly depicts the degree of isolation, so it is an ensemble-based anomaly detection method. Moreover, it has high accuracy and high speed in processing big data, so it has been widely applied in industry. Common application scenarios include attack detection in network security, fraud detection in financial transactions, disease detection, and noise data filtering (data cleaning).

### C. STL MODELS

Among methods of understanding and predicting time series, there is another widely recognised long-period time series analysis method, that is, the seasonal trend and LOESS (STL) method. In this method, it is assumed that time series are composed of three types of temporal patterns, namely, 1) a trend, the long-term growth or decline of the data, 2) the latent periodicity of the data, and 3) the residual or remaining part of the data. A time series can be formed by combining these three modes in different ways to ensure that the time series can be reversed or split and that outliers can be screened out through the outlier test.

Here, a space target (arbitrarily selected, NORAD-ID: 43651) is taken as an example to analyse its historical orbit data (from July 1, 2020, to January 1, 2022), and its spatial position information is obtained as depicted in Fig. 3 below.

**Fig. 3.** The space position trajectory diagram of the space object (NORAD ID: 43651) (1 July 2020-1 January 2022).
III. METHODOLOGY AND MODELS

A valid solution method is urgently needed for the problems facing SDA. This paper proposes a change-point detection method for space target sequential data streams, which can process massive data with real-time speed and obtain relatively accurate judgement results for space target states or behaviour. In this section, we describe the approach we propose for checkpoint detection of each satellite’s data stream.

A. PRELIMINARIES

By abstracting this problem as a mathematical problem, we can effectively define its solution. Here, we describe the problem through mathematical modelling. Specifically, the following definitions are given:

**Definition 1 (Time Series Data of Motion Features):**

$F$ sequences for each space target $V$ in each $G$ are given as vector sequences of the target features, from which we can extract motion features $f$. Here, we define the orbit measurement set for $f$, where $f \in \{1, 2, \cdots, F\}$.

In this study, we take motion features as a proxy for recognising satellite states. From the data stream acquired from the SSA equipment, the data of all the targets at a certain time can be determined; take the red points shown in Fig. 6 as an example. Since each satellite has several characteristics that are less common for other satellites, each satellite can be studied independently. In this section, we use the motion features of one satellite for selecting the data stream.

The orbit elements of one target can be selected as the blue diagram in Fig. 5.

We set the orbits of the satellites as the tensor $X$.

$x_{t/V} \in \mathbb{R}$ represents the value of the $f$-th feature at node $V$ at time $t$. For node $V$, there is a time series set...
\( X_V = (\vec{x}_1, \vec{x}_2, \cdots, \vec{x}_k) \), which represents the motion features of node \( V \) in the time set.

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

| State* | Motion state | The details of the probable behaviour 1 |
|--------|--------------|----------------------------------------|
| \( A_1 \) | normal | Normal operation |
| \( A_2 \) | abnormal | Orbit maintenance |
| \( A_3 \) | abnormal | Orbital manoeuvre with a sufficient impulse force (special emergency operation) |
| \( A_4 \) | abnormal | Mechanical malfunction |

*Normal operation means the satellite is in a regular state with no unusual change; orbit maintenance represents an impulse applied by the satellite to correct its orbit to maintain its preset orbit setting; an orbital manoeuvre represents the impulse applied by the satellite to change its orbit and enter another orbit; a mechanical malfunction means that something unusual and unpredictable has happened to the satellite.

In our study, we adopt the Time2Graph model [22], [23], [24] to recognise interpretable states from satellite time-series data, which are shown to be effective in handling noise and providing good interpretability. To solve the problem, the shapelet is mapped back to the time sequence to explore the position sensitivity, and the transfer relationship changes over time. A graph is constructed to represent it, forming an inferential and explicable method for change-point detection. Here, we modify this model to accommodate satellite motion recognition for behavioural cognition through the data stream, as shown in Fig. 7.

**B. TIME-AWARE FEATURE EXTRACTION OF THE TIME-SERIES DATA STREAM**

Since the motion of a space target is usually regular and basically stable, the temporal dataset of its motion characteristics is very regular and periodic. To save computing power, due to the strong interpretability of the shapelet, we first process the time series data stream and extract a shapelet that can represent its characteristics.

To capture the dynamics of the shapelet, two factors are defined to measure the temporal influence of the shapelet at different time locations. Specifically, we define a local factor picture to represent the internal importance of the n-th element of a particular shapelet. The distance between the shapelet and a sequence fragment can be defined as follows:

\[
\hat{d}(v, s|w) = \tau(v, s|a^*, w) = \left( \sum_{k=1}^{p} |w_{a_i}(k)| \cdot (v_{a_i}(k) - s_{a_i}(k))^{2} \right)^{1/2} \tag{2}
\]

Here, \( w \) is the local factor we set to denote the inner importance of the n-th element of a particular shapelet. \( \hat{d}(v, s|w) \) is the distance between a shapelet \( v \) and a segment \( s \).

\( a^* \) refers to the best alignment for DTW [25].

\( \tau(s_1, s_2|a) \) is the predefined dissimilarity for two sequences under the alignment.

Then, the distance between a shapelet \( v \) and a time series \( t \) can be rewritten as follows:

\[
\hat{D}(v, t|w, u) = \min_{1 \leq k < m} u_k \cdot \hat{d}(v, s_k|w) \tag{3}
\]

where \( t \) is divided into \( m \) segments; i.e., \( t = \{s_1, \cdots, s_m\} \).

Given a classification task, we establish a supervised learning method to select the most important time-aware shapelets and learn the corresponding timing factors, \( w \) and \( u \), for each shapelet, \( v \). In particular, we have a pool of segments as shapelet candidates that are selected from among all subsequences and a set of time series \( T \) with labels. Here, we set the objective functions as follows:

\[
\hat{L} = -g(S_{A_1}(v, T), \cdots, S_{A_4}(v, T)) + \lambda \|w\| + \varepsilon \|u\| \tag{4}
\]

\( \lambda \) and \( \varepsilon \) are the hyperparameters of the penalties, while the function \( g() \) measures the distances between distributions for the classified sets. After learning the timing factors from the shapelet candidates, we select the top **K** shapelets with minimal loss in Eq. (4).
C. Constructing the Shapelet Evolution Graph

After being extracted from the time series data stream, the shapelet is transformed into a graph model. Due to the convenience of the graph structure for the relative calculation, the corresponding shapelet and its time segments are correlated and calculated from the graph model to determine information about the time series represented.

First, the shapelet set is transformed into a directed weighted graph \( EG=(V,E) \). Each shapelet yields \( k \) vertices of the graph \( EG \) as \( v_i \in V \), where each \( v_i \) followed by \( v_j \) forms an edge from \( v_j \) to \( v_j \). In addition, the weight of the edge \( \omega_{ij} \) is the probability that \( v_i \) will be followed by \( v_j \).

We denote the shapelets assigned to segment \( s_i \) as \( v_{i,s} \) and say that \( v_{i,j} \) is the \( j \)-th assignment of \( s_i \). To measure how reasonable our assignment is, we standardise the assignment probability \( p_{ij} \) as follows:

\[
p_{ij} = \frac{\max(\hat{d}_{i,s}(v_{i,s}, s_i)) - \hat{d}_{i,s}(v_{i,j}, s_i)}{\max(\hat{d}_{i,s}(v_{i,s}, s_i)) - \min(\hat{d}_{i,s}(v_{i,s}, s_i))}
\]  

(5)

It is subject to predefined constraints as follows:

\[
\hat{d}_{i,s}(v_{i,s}, s_i) = u_s[i] \ast \hat{d}(v_{i,s}, s_i|w_s)
\]  

(6)

Then, we have \( \hat{d}_{i,s} < \delta \).

For each pair of shapelets \( (j,k) \), \( v_{i,j} \) is followed by \( v_{i+1,k} \) with the weight:

\[
\omega_{ij} = p_{ij} \ast p_{i+1,k}
\]  

(7)

Finally, the edge weights obtained from each node are normalised to 1, and they are naturally interpreted as the edge weights between each pair of nodes.

Algorithm 1 Shapelet Evolution Graph Construction

**Input:**
- time series set \( T = \{t_1, \ldots, t_T\} \)
- \( K \) Shapelet \( \{v_1, \ldots, v_k\} \)
- distance threshold \( \delta \)

**Output:**
- Shapelet evolution graph \( G \)

1: Initialize the graph \( G \) with \( K \) vertices
2: for all segment \( s \) of \( t \) in \( T \) do
3: for all shapelet \( V_j \) where \( \hat{d}(v_j, s|w_j) \ast u_j[i] \leq \delta \) do
4: Assign \( v_j \) to \( s_i \) with probability defined in Eq. (8)
5: end for
6: end for
7: for all adjacent segment pair \( (s_i, s_{i+1}) \) of \( t \) in \( T \) do
8: for all assigned shapelet pair \( (v_{ij}, v_{i+1,k}) \) do
9: Add directed edge \( e_{j,k} \) with weight \( p_{ij} \ast P_{i+1,k} \)
10: end for
11: end for
12: Normalize the edge weights for each vertex
13: return \( G \)

D. Representation Learning

After the graph model with the information of every shapelet has been constructed, the representation learning algorithm can be used for calculation. A graph embedding algorithm (such as DeepWalk [26]) can be adopted to obtain the graph representation.

Using the graph algorithm, each pair of shapelets \( v_{ij} \) is embedded into a vector \( \mu(v_{ij}) \). By multiplying by the assignment probability \( p_{ij} \), all of the values are summed for each segment. Finally, all the embedding vectors are joined or aggregated to obtain the representation vector of the original time series.
The learned representation vectors are applied to various downstream sequential tasks. Therefore, as the anomaly score is determined from the representation vector or calculated from the requirements of the graph model by analysis, the checkpoint is judged by a certain threshold value. An abnormal point can be considered to be a value greater than a certain threshold to judge the state of the satellite.

**IV. EXPERIMENTS**

In this section, the method proposed in our study is verified by a simulated satellite in-orbit data stream. That is, through the on-orbit target timing dataset, we can quickly obtain a relatively accurate detection conclusion regarding the change point, which provides informational support for judging its state.

**A. EXPERIMENTAL SETTINGS FOR DETERMINING METHOD VALIDITY**

As the input for the laboratory setting of the space target track in studying the effectiveness of the method and time series data stream in this paper, to construct a satellite orbit in a regular and routine operation mode, such as that of a LEO satellite, each of the orbital maintenance activities is marked to obtain the universal space target satellite data flow ST. First, the explicit features of the ST data are analysed, as shown in Fig. 8.

Due to the universality of the orbit and the operation mode of satellite S, we verify the validity of the method proposed in this study through comparative experiments. We compare our proposed method with several groups of baselines: feature-based models, forest models, and STL models.

**B. COMPARISON WITH FEATURE-BASED MODELS**

Here, we use feature-based models to calculate the data. We divide the dataset into 80% and 20% segments, and the accuracies of several obtained models are shown in Table 2 below.

| Model       | Accuracy | Time consumption |
|-------------|----------|------------------|
| Logistic Regression | 0.999031 | 0.24 s           |
| AdaBoost    | 0.998909 | 1.62 s           |
| GBDT        | 0.998183 | 5.56 s           |
| XGBoost     | 0.999031 | 1.57 s           |
| LightGBM    | 0.998788 | 2.38 s           |

In addition, we calculate the specific XGBoost model performance, and the results are shown in Table 3 and Fig. 10.

In Fig. 9, the change points can be seen clearly. A total of 9 change points among 10321 points appear in the series, but they are missed by feature-based models, such as XGBoost. Therefore, these types of methods are unable to detect outliers.
FIGURE 9. The performance of XGBoost: (a) the log loss of the model; (b) the classification error of the model; (c) the outliers in the space target data marked with red lines. These are the actual positions of the target marked for orbit change.

FIGURE 10. Through the method proposed in this paper, the SCT2G model is designed to detect the change points of the spatial target data stream, and the red lines indicate the outliers (model parameters: N-node = 200, x-Anomaly = 0.986).

TABLE 3. Performance of XGBoost on space target data streams.

| Indicator | Precision | Recall | F1-score | Support |
|-----------|-----------|--------|----------|---------|
| 0         | 1.00      | 1.00   | 1.00     | 2064    |
| 1         | 0.00      | 0.00   | 0.00     | 1       |
| Accuracy  |           |        | 1        | 2065    |
| Macro avg | 0.5       | 0.5    | 0.5      | 2065    |
| Weighted avg | 1.00 | 1.00 | 1.00 | 2065 |

Since space targets are moving regularly almost all the time, it is difficult to predict only a few sets of change points (due to orbit manoeuvring, machine failure, etc.), the accuracy is almost 100%, and there is no research value in anomaly detection. This is not acceptable and with no possibility in the real world.

Therefore, in contrast to the complete failure of these methods in abnormality detection, the method proposed in this paper can detect change points. As shown in Fig. 10, the method proposed in this paper yields obvious detection results of change points and can effectively detect the space target motion trajectory change points.

C. COMPARISON WITH FOREST MODELS

The isolation forest algorithm is used to detect abnormal points. Here, we use the isolation forest model to determine the space target change points for comparison with the method proposed in this paper. In the isolation forest
The algorithm experiment, the optimal model parameter setting is obtained by adjusting the parameters, and the isolation forest model based on the optimal parameter setting is used to perform detection on satellite timing data. As shown in Fig. 11, in 11-(b), the outliers are 9 times the size of the normal points to highlight the effect. In 11-(c), the degree of the outliers can be determined by the score of each data sample, and it can be clearly seen that the number of outliers calculated by the optimised isolation forest model is still large.

The results of the isolation forest algorithm show that it has change-point detection capability, but its detection accuracy is not high. We compare the outliers identified by the isolation forest algorithm with those identified by the algorithm proposed in this paper in Fig. 12. We can clearly see the recognition accuracy advantage of the method proposed in this paper.

**D. COMPARISON WITH STL MODELS**

Among the anomaly detection methods for long-period time series data, such as STL models, the robust STL [27] model published in AAAI 2019 is more advanced and widely applicable.

Robust STL is an improved method based on the idea of the STL algorithm. It is a robust and general method of periodic trend decomposition that can accurately and effectively extract seasonal features from data with long seasonal periods and large noise. In particular, it allows flexibility and movement of seasonal components that change over time. Sudden changes in the trend and remainder can also be handled well. The trend component is robustly extracted by using a minimal absolute deviation loss with sparse regularisation to solve the regression problem. Based on the trend of extraction, nonlocal seasonal filtering is applied to extract seasonal components.

This process is repeated until the optimal solution is obtained, which is an accurate estimate of the trend/seasonality. Therefore, the proposed robust STL seasonal trend decomposition method is an ideal tool for extracting rules from time series data for anomaly detection.

Therefore, we conduct a TSL model experiment on the same space target data, and the analysis of the model results
FIGURE 12. Comparison diagram of the change point detection results of the spatial target data stream (from top to bottom, the results of the real data points, the results of change-point detection by the isolation forest algorithm, and the results of change-point detection by the algorithm proposed in this paper).

FIGURE 13. Processing results of space target time series data based on the robust STL model. From left to right: the data analysis results of the sample, trend seasonality and remainder.

obtained through long-term optimal parameter calculation is shown in Fig. 13.

In this process, a large computing cost and time cost are incurred. A comparison of the time consumption is shown in Table 4.

TABLE 4. Change-point detection performance of the robust STL model and the SCT2G model proposed in this paper for the same space target data.

|                | ROBUST STL | SCT2G  |
|----------------|------------|--------|
| Accuracy       | 0.7653     | 0.8121 |
| Time consumption | 5307.34(s) | 2.59(s)|

However, given the requirements of the SDA applications in this study, the time sensitivity index should be considerably important in processing space time series data. That is, without substantial accuracy optimisation as a result of the other models, the time consumption is the most important reference we considered for model selection. Therefore, the method proposed in this paper is superior to other models, with excellent accuracy and low time consumption, meeting the real-time data processing requirements of SDA for massive spatial objects.

V. APPLICATIONS

In this section, we carry out a practical application of the method proposed in this paper to further illustrate the effectiveness and superiority of this method.

A. APPLICATION TO GIANT LEO CONSTELLATION

Due to the design and implementation of low-orbit mega-constellation projects (Starlink, OneWeb, etc., as shown in Fig. 14) by SpaceX, OneWeb and others, low-orbit space contains tens of thousands of space targets, and this trend will continue in the future. Using the original astrodynamics method will consume too much computational cost and reduce the time sensitivity of space manageability.

However, this method can be used to implement anomaly detection for massive spatial targets with less computational cost and very low time cost. The results can yield a rough description of the space situation and can then be combined with a subsequent precision model to conduct further specific research on the screened outliers to synthesize the lowest cost and effectively determine the situation of the space domain.
in real time. We select a satellite in Starlink (NORAD-ID: 45181, taken as an example) to analyse its motion trajectory as obtained by the method in this paper.

First, we process and display the satellite trajectories obtained from July 1, 2020, to July 1, 2022, as shown in Fig. 15. It can be seen that the satellite operates regularly and maintains a stable orbit almost all the time. Therefore, the SCT2G model in this paper is used to calculate the satellite position and velocity. The result is shown in Fig. 16.

From the yellow lines, we can analyse and determine the changes in the satellite’s states. If there is a major anomaly...
FIGURE 17. Results of the abnormal scores (yellow lines) of the norms of position and velocity marked as red outlier lines (node = 50, threshold value = 0.7958, 0.75) calculated by the SCT2G model.

FIGURE 18. Satellite (NORAD ID: 44797) trajectory from January 1, 2020, to January 1, 2022, displayed based on the acquired data.

FIGURE 19. Results of the abnormal scores (yellow lines) of the norms of position and velocity marked as red outlier lines (node = 50, threshold value = 0.7958, 0.75) calculated by the SCT2G model.

and the satellite trajectory jumps, the model interpretation results output by the SCT2G model will be considerably different from other historical values. It can be seen that the satellite did not have a large range of orbital manoeuvre events.

However, we can still select some points from the model results that are slightly higher than the average daily value, and determine that space orbit maintenance activities may have been carried out (only within the scope of consideration). After inputting the square root of the position vector and the square root of the velocity vector into the SCT2G model for calculation, the results are shown in Fig. 17. The areas with red lines are the ranges of abnormal points to be considered.

FIGURE 20. A visualisation of satellite 44797 approaching KH-11 obtained from a news report.

Here, we can select some points that may be abnormal through the model. However, further analysis is needed to
determine whether the satellites carried out orbit maintenance activities. However, the basic time needed for this process is less than 1 s, so it has excellent application value and is worth adopting for SDA activities.

B. APPLICATION TO ORBIT MANOEUVRES

Above, we applied the orbital data of low-orbit satellites in conventional operation. Next, we will conduct an experiment applying the method proposed in this paper to satellites that frequently undergo orbital manoeuvring. The data of a space target with frequent orbital manoeuvring events are analysed, and the data are processed by the algorithm proposed in this paper to determine whether the results can enable detection of anomalous satellite orbit data (NORAD ID: 44797) from January 1, 2020, to January 1, 2022, as shown in Fig. 18 below.

Similar to Section 5.1, we calculate the norms of the position and velocity vectors to represent position and velocity features, respectively, and then apply the method proposed in this paper to the norms of position and velocity. The anomaly detection results obtained are shown in Fig. 19.

According to the model calculation results, the anomaly value of the satellite’s position norm is very important from January to February 2020, from October to November 2021, and in May 2020, August 2020 and June 2021. This means that at these times, the satellite was performing orbital manoeuvring activities. Among those times, we can see that the anomaly values from January to February 2020 and from October to November 2021 were frequently out of range. This may be evidence that the satellite performed a series of orbital manoeuvre activities from January to February 2020 and from October to November 2021. Therefore, we determine that the satellite was aiming to complete a specific task.

Our judgement was objectively confirmed by news reports. According to the ‘war zone’ column of the Drive website, Cosmos 2542 underwent a series of manoeuvres to change its position and timing to match the “orbital period” of USA 245 starting on January 20, 2020, as Fig. 20 shows. It was announced that Cosmos 2542 changed its orbit near the KH-11 satellite on January 30. This news verified the conclusion of our anomaly detection method. However, through our method, we can not only go beyond this conclusion but also find more timely and credible abnormal orbital changes.

C. APPLICATION TO GEO SATELLITES

In this section, we calculate the data of GEO orbit satellites. We randomly choose a GEO satellite and apply the method proposed in this paper to the orbital data stream of the satellite (here, the chosen satellite is NORAD-43651) from January 1, 2020, to January 1, 2022. Due to the large amount of data, over 150,000 data points, the first 1600 time sequence orbit samples were selected for calculation, and the detection results of the change points were obtained as shown in Fig. 21. We can clearly see that change points can be detected effectively for a satellite with regular motion through the method proposed in this paper.

VI. DISCUSSION AND CONCLUSIONS

To address related problems and challenges in SDA activities and research, this paper clarifies the problem statement of space target behaviour analysis. We believe that change-point detection in space target data streams can aid the understanding and cognition of space situations in a faster, more comprehensive and more scientific way. Therefore, we construct a change-point detection method for space target data streams based on the T2G model and verify the effectiveness and performance of the method through simulated satellite data streams. It is proven that the method proposed in this paper can quickly and effectively detect the change points of a civilian space target. Furthermore, preliminary conclusions regarding space target behaviour are drawn by analysing the calculated anomaly score. After verifying the method, we demonstrate its applications in several important fields (such as regular LEO satellites, LEO satellites with frequent orbit manoeuvres, and GEO satellites), which not only verifies the effectiveness of the method proposed in this paper but also helps to obtain much more space information through analysing the model results. This model can provide valuable evidence, recommendations and references for subsequent space situation analysis and space mission planning.

In summary, the method proposed in this paper can perform rapid, scientific and effective change point detection for the data streams of space targets, and the relevant behaviour or activity of space targets can be analysed in real time through the detection results to yield a faster, more comprehensive and more accurate understanding of space situations and lay an important foundation for subsequent space activities.
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YINING SONG received the B.S. degree in mathematics and applied mathematics from the University of Science and Technology of China (USTC), Anhui, China, in 2010, and the M.S. degree in systems science from Space Engineering University, Beijing, in 2012, where she is currently pursuing the Ph.D. degree in aerospace science. From 2010 to 2012, she was a Research Assistant at Space Engineering University. Her research interests include the development of space power and conduction using the latest technology. She is also focusing on the technology of space domain awareness.

ZHILI was born in 1973. He received the master’s degree from the National Defense Science and Technology University (NUDT), in 2001, and the Ph.D. degree from China Earthquake Administration, in 2003. He is currently a Professor and a Ph.D. Supervisor with Space Engineering University. His research interests include space system administration and SSA.

ZHANYUE ZHANG was born in 1974. He received the Ph.D. degree from the National Defense Science and Technology University (NUDT), in 2005. He is currently a Professor. He is also a Supervisor at Space Engineering University of PRC. His research interests include space security.