Progress and Challenges in Intelligent Remote Sensing Satellite Systems

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***Abstract*—Due to advances in remote sensing satellite imaging and image processing technologies and their wide applications, intelligent remote sensing satellites are facing an opportunity for rapid development. The key technologies, standards, and laws of intelligent remote sensing satellites are also experiencing a series of new challenges. Novel concepts and key technologies in the intelligent hyperspectral remote sensing satellite system have been proposed since 2011. The aim of these intelligent remote sensing satellites is to provide real-time, accurate, and personalized remote sensing information services. This article reviews the current developments in new-generation intelligent remote sensing satellite systems, with a focus on intelligent remote sensing satellite platforms, imaging payloads, onboard processing systems, and other key technological chains. The technological breakthroughs and current defects of intelligence-oriented designs are also analyzed. Intelligent remote sensing satellites collect personalized remote sensing data and information, with real-time data features and information interaction between remote sensing satellites or between satellites and the ground. Such developments will expand the use of remote sensing applications beyond government departments and industrial users to a massive number of individual users. However, this extension faces challenges regarding privacy protection, societal values, and laws regarding the sharing and distribution of data and information.**

***Index Terms*—Artificial intelligence, hyperspectral remote sensing, intelligent remote sensing satellite, onboard real-time processing.**

I. Introduction

SINCE 2000, space remote sensing technologies have played an important role in resource surveying, urban planning, agricultural development, national security, and other related areas. With the continued progress in satellite remote sensing manufacturing and chip process technologies, the resolution of remote sensing satellite data is increasing in the spatial, spectral, and time dimensions. Intelligent processing technologies and computing power for datasets are also rapidly developing. These changes represent the arrival of a new era of remotely sensed big data [1], [2]. However, it also presents new problems, such as the insufficient upstream and downstream transmission bandwidth of satellite remote sensing data, the lack of adaptability of the remote sensing payload imaging method to complex ground and features changes, and time-efficiency problems of information services. Conventional satellite remote sensing data processing and application modes cannot adapt to the current demands for high time efficiency, personalized remote sensing data collection, and information product output. New key technology concepts for intelligent hyperspectral remote sensing satellite systems have been proposed and discussed since 2011 [3], with satellite imaging mode adaptive observation and onboard real-time data processing and distribution emerging as the two most significant technologies for intelligent hyperspectral remote sensing satellites (see Fig. 1).

Over the past decade, building a next-generation intelligent remote sensing satellite system has become the main target of China, the United States, and the European Union. Remote sensing satellite development has been established using launched remote sensing satellites with intelligent components, including the TacSat-3 (USA, 2009), TET-1 (Germany, 2012), new technology demonstration satellite G (China, 2020), and a high-resolution multimode satellite (China, 2020). With the improvement of onboard computation, data storage, and other resources, the on-orbit data computation of a single satellite is no longer restricted to simple processes of data compression or preprocessing. Thus, the processing chain is expanding to provide continuous client applications, including on-orbit target detection and identification. The intelligence level of remote sensing satellites with *one satellite for multiple applications, multisatellite mission integration* is improving continuously. Additionally, countries, industries, personalized clients, and other users present new remote sensing information accuracy and time efficiency requirements. Satellite information services are moving from large-scale ground stations to on-vehicle, onboard, and hand-held terminals for receiving and transforming. Therefore, the corresponding remote sensing satellite platform

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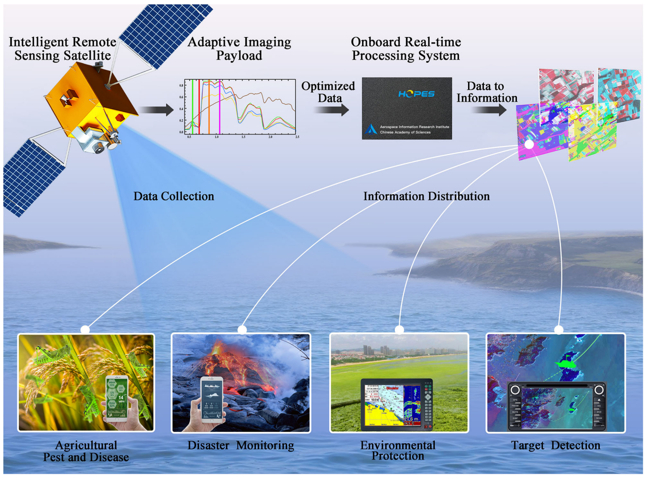

Fig. 1. Intelligent remote sensing satellite systems.

must be flexible, and the imaging mode needs to be adaptively optimized. On-orbit real-time data processing by satellite and direct satellite communications of personalized information are also required. In addition, the development and innovation of new technologies will present new challenges to social values and laws that must be addressed.

II. Key Advances in Intelligent Remote Sensing Satellites Over the Past Decade

The rapid development of key technologies, such as the remote sensing satellite platform, imaging payload, and onboard processing systems required for the construction of the intelligent remote sensing satellite system, is transforming the sphere of remote satellites from data sensing from earth observations to the real-time perception of targets.

A. Remote Sensing Satellite Platform

In order to achieve time-continuous and multiangle observations of any target of interest in the world, remote sensing satellite observation programs launched by various countries are evolving from single independent remote sensing satellites to multisatellite networking and collaborative observation, real-time communication between high and low orbit satellites, convenient data receiving, and so on.

1) Remote Sensing Constellation: To ensure remote sensing satellites can complete global monitoring tasks, including in Antarctica and Arctic regions, any place on the earth must be covered by remote sensing satellites at all times. Currently, the RapidEye constellation of Planet Labs (USA), composed of five satellites, can acquire up to four million square kilometers of multispectral images every day. The RADARSAT Constellation launched by SpaceX for the Canadian Space Agency in 2019 contains three to six small satellites. After the constellation is fully deployed, the ability to revisit Canada and the Arctic coast every day and distribute near-real-time data within half an hour will be achieved. BlackSky constellation includes a total of seven remote sensing small satellites with resolution of 0.85–1.3 m per pixel, distributed at different orbital altitudes and inclination angles, and can provide submeter-level images every day from any location in the world. Digital Globe's commercial remote sensing satellite WorldView constellation is composed of 12 satellites in sun-synchronous orbit and earth's mid-latitude orbit. The revisit period is up to 40 times per day. Planet Labs' miniature remote sensing satellite Flock has more than 150 satellites in orbit and can obtain anywhere in the world daily remote sensing images with a resolution of 3 to 5 m per pixel.

China's High-Resolution Earth Observation System (CHEOS) and commercial remote sensing satellite constellations are also rapidly developing. CHEOS began with the launch of the Gaofen-1 satellite in 2013. There are fourteen different types and 24 remote sensing satellites in orbit, forming a high spatial resolution, high temporal resolution remote sensing earth observation system. The Beijing-2 constellation launched in 2015 and is composed of three high-resolution satellites that can monitor any target on a global scale and return daily observations. The Jilin-1 constellation launched by the Chang Guang Satellite Company is expected to complete a network of 138 satellites by 2030 [1].

The goal of intelligent remote sensing satellites is to provide real-time accurate remote sensing information services. As single satellites cannot achieve this goal, multiple sets of satellites with different inclination angles and heights must be designed and configured into interconnected remote sensing satellite constellations to cover any location at all times. The current remote sensing constellations that are continuously being launched into orbit in China and abroad provide basic platform support for the development of intelligent remote sensing communication satellites in the future.

2) Inter-Satellite and Satellite-Ground Communication: The continuous implementation of the remote sensing satellite constellation program has led to breakthroughs in large-scale data transmission technologies, such as intersatellite and satellite-ground communication. Research on the space information network of space-earth integration has been successively carried out to coordinate the inter-satellite and satellite-ground communication. Recently, the United States presented the Transformational Satellite Communications System (TSAT) [4] and Space Common Data Link [5], while China proposed the concept of space-earth remote sensing information integration [6], which consists of space-based and land-based observation techniques.

Intersatellite laser communication technology has attracted increasing attention due to its large bandwidth, small size, light weight, low power consumption, good confidentiality, and lack of spectrum limitation. A number of high/low orbit technology verifications have been successfully completed, and the technology has entered the stage of scale construction and application. In 2015, the second-generation Laser Communication Terminal carried by the European Data Relay Satellite (EDRS) realized the Geostationary Earth Orbit (GEO) Low Earth Orbit (LEO) high-speed satellite laser communication test, with a Binary Phase Shift Keying modulation method, a communication distance of 45 000 km, and a transmission rate of 1.8 Gb/s. The ILLUMA-T project in the United States aims to establish a two-way communication link between GEO-LEO, with a communication rate of 2.88 Gb/s, and a communication standard compatible with Differential Phase Shift Keying and Pulses Per Minute.

In terms of satellite-ground communication networks, China's Tianlian, Queqiao, and Tiantong series backbone network constellation Ka-band ground communication rate can reach up to 300 Mb/s. Japan's Data Relay Test Satellite system can reach up to 240 Mb/s in the Ka-band ground communication, while the EDRS system can obtain a Ka-band ground communication rate of up to 300 Mb/s. The United States Tracking and Data Relay Satellite system and the Starlink, which is currently under construction, can reach a Ka-band ground communication rate of 800 Mb/s. However, space spectrum resources that can be used in the future remain relatively limited, where the mature L, S, C, Ku, and other frequency bands are almost completely occupied, and the use of the Ka frequency band is becoming increasingly tense. Direct satellite-ground laser communication can double the satellite and ground data transmission rate, thereby alleviating radio frequency restrictions.

The rapid development of terrestrial 5G and 6G communication technologies in China's BeiDou Navigation Satellite System enabled the use of various types of miniaturized terrestrial data receiving stations including ship-borne, vehicle-mounted, and handheld terminals, resulting in a convenient data receiving system. The lightweight image information extracted by the remote sensing satellite can be received in real-time to realize integrated sensing services of target location with real images based on the intelligent remote sensing satellite system. Driven by the concept of intelligent remote sensing satellite real-time sensing services, various new satellite platforms are constantly being designed and presented for orbit verification. Hundreds of large-scale satellite remote sensing observation networks are expected to emerge, and revolutionary technological developments will occur in the fields of large-scale remote sensing satellite operation management, multi-load cooperative observation, onboard real-time data processing, and convenient data receiving terminals.

B. Imaging Payload

The spatial resolution and imaging width of hyperspectral remote sensing satellite sensors have been greatly improved over the past decade. China's Gaofen-5 satellite can cover the electromagnetic wave in the range of 400–2500 nm, with a spectral resolution of 5 nm and an imaging width of 60 km. The spatial resolution of the SHALOM hyperspectral remote sensing satellite, jointly developed by Italy and Israel, can reach 10 m, and the DESIS hyperspectral satellite developed by the German Aerospace Center has a spectral resolution of 2.5 nm. The intelligent development of the imaging payload is reflected in adaptive imaging and multiload collaborative design.

1) Adaptive Imaging: Due to the constraints of the satellite remote sensing load imaging principle, there is a mutually exclusive relationship between spatial resolution and spectral resolution indicators. The pursuit of a higher spatial resolution will reduce the spectral resolution, and the pursuit of a higher spectral resolution will inevitably lead to a decline in the spatial resolution. Meanwhile, the data signal-to-noise ratio (SNR),

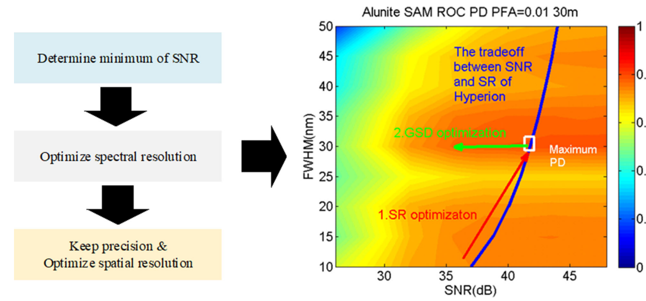

Fig. 2. Adaptive imaging model parameters.

as the core indicator that affects the accuracy of ground detection and recognition, also affects their restrictive changes. To address this, a load adaptive imaging mode has been proposed for intelligent remote sensing observation. Driven by the observation object and information extraction model [7], remote sensing sensor imaging parameters for orbit intelligent optimization have been employed to improve the accurate information extraction ability of ground objects.

Taking the remote sensing information extraction of altered minerals as an example, the initial data SNR is first determined. Under this SNR condition, load imaging data can meet the minimum requirements for mineral classification and identification. The spatial resolution and spectral resolution observation index optimization can, then, be achieved through the following steps (the process on the left side of the Fig. 2).

1) Determine the optimal spectral resolution, substitute the changes of data SNR and spectral resolution into the classification and recognition model of minerals [8], and develop the change curve of the spectral resolution-information extraction accuracy to evaluate and determine the optimal spectral resolution.
2) Adjust the spatial resolution to maximize the spatial resolution under the conditions of determining the data SNR and spectral resolution.

If the initial SNR does not meet the minimum requirements for mineral classification and identification, it is necessary to reduce the spectral or spatial resolution to increase the SNR. When the SNR is increased to meet the minimum requirements of mineral extraction, the observation indexes of the remote sensor are optimized through the abovementioned steps.

Taking the Hyperion remote sensor index as a reference, the proposed adaptive imaging model was used to optimize the observation index. The hyperspectral data was simulated based on the optimized remote sensing sensor index, and the extraction results of typical altered minerals before and after index optimization were compared. Changes in the detection accuracy under certain false alarm rates were analyzed, and the effectiveness of adaptive imaging was verified (the results are shown on the right side of the Fig. 2). As shown in the image, under different altered minerals and application model conditions, the recognition accuracy improved by the intelligent optimization of remote sensor parameters is different. In general, the average detection accuracy of six typical mineral parameter optimization images, such as kaolinite, alunite, muscovite, calcite, chalcedony, and buddingtonite is 19.5% higher than that of the Hyperion simulation images.

Considering the difficulty of on orbit real-time adaptive imaging, it is also feasible to select and correct the sensitive band through soft adjustment after imaging. Recently, some intelligent methods have provided lightweight artificial neural networks or efficient online algorithms to achieve real-time image quality improvement [9], which have significant potential for further application in on-orbit soft adjustment after imaging. Unlike the image processing model with fixed hyperparameters, Rui *et al.* [10] proposed a method based on the meta-knowledge learning-driven adaptive removal of hyperspectral image complex noise to improve data SNR, which had good scalability. Li *et al.* also proposed a lightweight on-orbit blind denoising network and a boundary enhancement network to improve the quality of remote sensing images. The networks were configured with the same computing resources (6 GB RAM, 64 GB ROM, and 8 Snapdragon processors) on the Tianzhi-1 satellite to improve the semireal-time data SNR [11], [12]. In particular, for cloud screening, the on-orbit processing takes the raw instrument data values as the object and needs to process data throughput up to the order of Gbps. Thompson *et al.* [13] proposed an effective online cloud screening method and applied it to the airborne AVIRIS-NG platform successfully. In the next step, it will also be deployed on an earth-orbiting spectrometer satellite.

2) Multiload Coordination: At present, when designing the main imaging load of a hyperspectral remote sensing satellite, a fixed radiation dynamic range will lead to a large number of invalid and redundant data, resulting in significant data storage, transmission, and processing pressure. Based on the traditional main imaging load, a front camera can be added to assist the main load imaging and used to assist the hyperspectral camera imaging for dynamic range adaptive adjustment to realize multiload efficient cooperative imaging [14].

Multiload satellites have performed in-orbit verification of real-time cloud judgment in situations where a large amount of invalid data collection was caused by thin cloud interference. The hyperspectral imaging payload of China's Gaofen-502 satellite and a high-resolution multimode satellite were designed with synchronously equipped aerosol detectors to observe the distribution of absorptive aerosols from the ultraviolet band. This avoids the problem of acquiring the imaging area with a large number of clouds, and the effective data acquisition rate of the main load is enhanced.

Although the imaging payload technology has been significantly improved in the single image index, the practical application of adaptive imaging technology is low, and the degree of intelligence is insufficient. Imaging technology remains in the soft adjustment stage, requiring the manual injection of *a priori* information and time-sharing conversion of the imaging mode. Therefore, the implementation of adaptive imaging must start from the application. Taking the maximization of effective information as the optimization goal and comprehensively considering the influence of the imaging mechanism, ground object type, and other factors, an imaging parameters library for different monitoring needs must be established to improve the proportion of effective remote sensing information and imaging quality.

C. Onboard Processing System

Onboard real-time data processing is one of the most prominent features of the intelligent remote sensing satellite system and is unlike conventional onboard data compression (*from big data volume to small data volume*). Onboard data processing works to directly convert the acquired remote sensing image into effective target information (*from data to information*) in-orbit to meet the requirements of highly time-effective remote sensing applications.

1) Onboard Processor Chip: The rapid development of large scale integrated circuit technology in the past ten years enable the processor chips achieved smaller size, lower power consumption, and stronger computing ability. These advances enable remote sensing image information extraction to be realized in real time on satellites, which was not possible before, considering that the process is data and computationally intensive. In addition, the low total ionization dose and low probability of single-particle flipping in the near earth orbit space environment (such as 400 km altitude) enable traditional high-cost aerospace-grade chips could be replaced by industrial-grade chips for onboard computing systems [15].

The NASA Goddard Space Flight Center designed the SpaceCube v3.0 processing system in 2019, using a Kintex UltraScale Field Programmable Gate Array (FPGA) and Xilinx Zynq Multiprocesser System on Chip as the core processing unit to achieve high-performance on-orbit reconstruction [16]. LEON series aerospace-grade processors designed by the European Space Agency (ESA) based on SPARC V8 have been used in satellite computers, such as the Iridium NEXT [17]. The 17th satellite of China's BeiDou navigation system is equipped with Loongson 1E and 1F anti-irradiation processors to complete data processing of the intersatellite link, and the performance can reach 200 MIPS [18]. The fourth group satellites of China's Zhuhai-1 mission plan to employ the Yulong series processor chips as the embedded onboard artificial intelligence computing platform. It is reported that the floating-point processing capabilities of Yulong410 and Yulong810 are 32 and 64 GFLOPS, respectively.

Processor chips with large-scale graphics processor GPUs as the core are also increasingly used in image remote sensing. The PhiSat-1, launched by the ESA in 2020, is equipped with a Movidius Myriad 2 visual processing unit. In its on-orbit intelligent cloud detection, cloudy images are discarded, and data downloads are reduced by 30% [19]. Slater *et al.* [20] conducted a total ionizing dose radiation test on the Jetson Nano, finding it could work in a space environment above 20 krad(Si), and its radiation tolerance was sufficient for short-term small satellite missions. China's Jilin-1 spectral satellite has realized GPU-based on-orbit automatic identification of forest fires and sea ships. Meanwhile, research for onboard data processing has gradually begun to explore edge GPUs, such as the Jetson TX2 (1 TFLOPs) and Xavier NX (11 TFLOPS) [21].

The processor chip is the core restriction to onboard processing capability, and the current aerospace-grade chip is very expensive and has limited production capacity. Facing requirements for a large number of remote sensing earth observation missions and low-cost needs, industrial-grade devices have begun to be gradually applied on intelligent remote sensing satellites in near earth orbit. These low-cost industrial-grade chips significantly improved the onboard remote sensing data processing capabilities. In the near future, a large scale application of industrial-grade devices in low-orbit intelligent remote sensing satellites could be one of the main trends in developing onboard processing systems. This can provide sufficient computing ability support for the rapid verification of constellation networks of novel intelligent remote sensing satellites.

2) Onboard Real-Time Information Extraction Algorithm: The single satellite on-orbit processing of remote sensing satellites is no longer limited to conventional data compression, radiation correction, geometric correction, and other preprocessing tasks. On-orbit processing of real-time information extraction functions such as target detection and change monitoring is already widely used.

The TET-1 and BIROS small satellites launched by the German Aerospace Center (DLR) as part of their FireBIRD project are the follow-up satellites to BIRD [22]. In addition to continuing BIRD's radiation correction, geometric correction, surface high-temperature event warning, fire spot monitoring, thematic map production, and in-orbit data processing capabilities, such as onboard real-time classification and the realization of ground training classification parameters [23], [24], the onboard data downlink [25] has also been enhanced. The Pleiades satellite was deployed after SPOT in France as a new type of high-resolution satellite. The satellite implemented radiation correction, geometric correction, image compression, and other onboard processing functions through an MVP modular processor with FPGA as the core [26]. In addition to daily observations of Singapore and Southeast Asia, Singapore's X-Sat satellite can also perform data collection and on-orbit processing in the Pacific and Indian Ocean regions [27] and can automatically eliminate invalid data in-orbit [28]. The Canadian RADARSAT satellite combines the automatic identification system and powerful radar images to realize onboard real-time ship detection and identification [29].

China has also conducted onboard remote sensing image processing experiments on different types of satellites. The Pujiang-1 satellite, independently developed by Shanghai Aerospace Technology Research Institute, has the fusion function of onboard preprocessing and data processing. It can distinguish, extract, and locate abnormal areas in orbit, and realizes the cooperative work of multiple payloads through onboard data processing autonomous task planning technology. The high resolution multimodal integrated imaging satellite launched by the China Academy of Space Technology has successfully completed target extraction, system radiation correction, Charge Coupled Device splicing, system geometric correction, and other processing by using a high-resolution multimode satellite on-orbit real-time image product processing system to generate Level 2 image products of the region of interest and quickly distribute them to the user terminal [30]. The Luojia 1-01 luminous remote sensing satellite developed by Wuhan University has realized on-orbit geometric calibration and relative radiometric calibration [31]. Chang Guang Satellite Company's Jilin-1 Spectrum 01/02 satellites are equipped with remote sensing emergency response on-orbit intelligent processing systems with automatic identification, search, and positioning functions for forest fires and ships at sea [32]. The new technology demonstration satellite G, launched by China in 2020, is mainly used to carry out onboard real-time remote sensing information extraction technology validation for earth observation missions.

In the intelligent processing mode, the conventional complex procedure "*uploading task, satellite imaging, receiving image, image processing, information analysis, and distribution*" will be optimized; users can directly receive customized remote sensing information in near real time through the mobile terminal. The time required for *"remote sensing satellite to end-user"* can be reduced from days to minutes, thus overcoming the core bottleneck of remote sensing information service for time sensitive applications.

3) New Computational Architecture for Hardware and Software Collaboration: Most of the existing onboard processing systems simply transfer the remote sensing data processing algorithms from on the ground to the satellite computing environment. Few systematically optimized designs were carried out for onboard real-time remote sensing information services. Specifically, for hyperspectral remote sensing satellites, one problem is the hundreds of image bands cased large volume of data size, the other problem is the high complexity radiometric calibration, spectral correction, and atmospheric correction procedures. It is hardly to achieve onboard real-time processing without systematic optimization design for specific targets. Therefore, the key to a breakthrough in the performance of onboard computing is the development of new computing architectures, such as information extraction algorithms for non-strict quantitative data processing and cross-level collaboration architectures of algorithm-software-hardware.

In order to solve the problem of real-time target detection on hyperspectral satellites, innovative computing methods and software-hardware collaborative optimization methods have been carried out. Wu *et al.* [33] applied embedded GPU to implement anomaly detection algorithms of hyperspectral data, and preliminarily verified the feasibility of onboard processing scenarios. Inspired by the error resilience exists both in data level and algorithm level of image classification and recognition, novel hardware architecture for approximate computing is proposed for reducing energy consumption in remotely sensed onboard processing tasks [34]. Subsequently, considering that the inherent high computation cost of the detection process severely restricts its processing efficiency, a spectral-spatial approximation computation was proposed to reduce the computational complexity of onboard hyperspectral anomaly detection [35]. He *et al.* [36] investigated onboard autonomous image processing platforms, such as onboard image processing, fusion, information extraction, and rapid location of suspected target regions, typical target recognition, and regional change detection.

With the increasing popularity of deep neural networks (DNNs) on the ground processing scenarios, the use of DNNs for target detection and other tasks has begun verification on satellites. The processing method has evolved from a shallow algorithm related to data preprocessing to an artificial intelligence (AI) approaches for target information extraction, and the onboard processing chain continues to expand. Meanwhile, with the evolution of efficient deep learning systems, such as model compression of DNNs, the development of specially designed AI chips will be more suitable for onboard remote sensing image processing tasks.

The onboard real-time data processing system is act as the brain center of the intelligent remote sensing satellite. Through the onboard real-time processing system, GB-level raw remote sensing images can be converted into KB-level target information of interests. Besides the basis of conventional satellite ground station data transmission, this KB-level target information could be transferred to the space-based routers through intersatellite laser communication, then can be quickly distributed to different end-users through the space-ground communication network. Guided by specific application requirements, the function of intelligent remote sensing satellites is to provide GPS-style remote sensing information services to improve the efficiency of remote sensing imaging and the utilization of remote sensing data [37].

III. Promoting the Development of Remote Sensing in Space

The development of intelligent remote sensing satellites has greatly promoted the development of remote sensing in aerospace. The traditional satellite-to-earth communication model relies on large-scale remote sensing satellite ground stations to directly serve an end-users unit. Conversely, intelligent remote sensing satellite information services are Internet-based and GPS-style to serve more end-users in a more convenient form. Thus, it can expand the use of remote sensing applications from government departments and industrial users to a huge number of individuals. To achieve this aim, the problems of timeliness, unbalanced distribution, and excessive data generation must be solved, as discussed in the following section.

A. Solving the Service Timeliness of Satellite Remote Sensing Data

In the field of natural disasters and environmental pollution accident monitoring, current satellite remote sensing methods mostly can be regarded as retrospective analysis. After remote sensing data is collected in orbit, it must pass through the subsatellite point of the ground station for data transmission due to its huge size. After the ground station receives the data, it is sent to the industry department for processing, and then the processing results are distributed to users. The entire processing chain usually takes several days, and the timeliness problem cannot be sped up when faced with emergency situations. Therefore, the timeliness of conventional remote sensing satellites is limited to the traceability of the event and cannot achieve real-time monitoring during the event. Meanwhile, with the increasing demand for earth observation from remote sensing, various mediums and low orbit satellites cause blockages in storage, distribution, information processing, and other remote sensing information traffic, which further reduces the timeliness of traditional satellite remote sensing data services. In order to meet the needs of real-time and customized remote sensing information services, intelligent remote sensing satellites process remote sensing data via onboard and space-earth integration approaches. The large volume of raw remote sensing images is processed on-orbit, and the target information can be distributed to all kinds of end-users through space-based and land-based interconnections to realize "*what you want and provide immediately*". Thus, the remote sensing data service time could be reduced from days to minute level to meet time-sensitive scenarios, such as national emergency and commercial applications.

B. Solving the Unbalanced Distribution of Satellite Remote Sensing Data

The conventional remote sensing satellite data service relies on large-scale data centers. Once all types of remote sensing data are gathered in the data center, standardized production of images at different levels is conducted. The data center then distributes these standardized images to industry departments for special information extraction. This distribution and usage model of remote sensing data is only applicable to major government industry sectors. With the development of remote sensing technologies, the demand for personalized commercial remote sensing is increasing, along with the demand for personalized remote sensing information services. It is also difficult for complex data processing and information extraction processes to meet the diverse needs of the remote sensing industry. Intelligent remote sensing satellite, relying on the integration of the space-earth network, is directly oriented to end-users through the overall coordination of satellites. Thus, a large number of intermediate interaction links are reduced, and data is available to users at all levels in an orderly manner, enabling the data to be fully utilized in various industrial stages of remote sensing.

C. Solving the Massive Waste of Satellite Data Storage Resources

End-users require effective information provided by remote sensing satellites, not a large amount of remote sensing data. The recent improvement in remote sensing load resolution and width has caused the size of remote sensing data to grow exponentially. For instance, China's remote sensing satellite ground stations, mainly located in Miyun, Sanya, and Kashgar, receive a huge variety of remote sensing satellite data. After decompression, the average size is 20 TB a day and nearly 7 PB a year. The remote sensing data size increases exponentially following radiometric correction, geometric correction, and reflectance inversion, at which point the amount of nonrepeated data storage will reach 20 PB. The storage, invocation, and production of these massive amounts of remote sensing images can be seen as high energy-consuming industry. Intelligent remote sensing satellites provide a new approach of efficient and accurate utilization of remote sensing data resources, alleviating remote sensing satellite data storage pressures while contributing to global sustainable development, energy conservation, and greenhouse gases emission reduction.

IV. Policy Issues to be Solved

A. Intelligent Remote Sensing Satellite Technical Standards and Specifications

Intelligent remote sensing satellites are characterized by real-time data and information interaction between remote sensing satellites and between satellites and the ground. This poses challenges for standard design specifications for intelligent remote sensing satellites. It is necessary to improve the technical management of intelligent remote sensing satellites and break the original technical barriers of separate construction of remote sensing satellite systems. Onboard information system equipment interface and soft hardware standards, onboard data transmission and communication protocol, onboard remote sensing data imaging and data standards, and onboard remote sensing data format parameters and grading classification standards must be unified, and intelligent remote sensing satellite ground resources must be combined in a modular configuration. These standards will provide a standard foundation for barrier-free interactions between intelligent remote sensing satellites and the overall planning of tasks. Such measures can also improve the timeliness of intelligent remote sensing satellite system coordinated earth observation missions and reduce the response time of emergency missions. The intelligent remote sensing satellite system resources can, then, be shared, the platform can be used universally, and tasks can be planned collaboratively to provide high-quality remote sensing information services to commercialized industries.

B. Laws and Regulations Related to the Use of Intelligent Remote Sensing Satellite

Intelligent remote sensing satellite acquires personalized remote sensing data and information, which inevitably raises legal issues regarding the sharing and distribution of data and information. In terms of data sharing, China has different management policies for various types of remote sensing satellite data. For example, there are differences in the distribution and sharing of spatial resolution and spectral resolution data among meteorology, oceanic, environmental, and other resources [38]. The remote sensing satellite data sharing policy was first promulgated in the United States, in which satellite remote sensing images with a resolution better than 0.31 m per pixel is prohibited from being shared [39]. Establishing a remote sensing satellite management mechanism with separate management and coordinated development is the guiding ideology of American aerospace activities. Europe's remote sensing data policy is based on sharing as the core to their ''*Earth Observation Science Strategy*'' released in 2015, which details the future development direction of earth observation. Sentinel series satellites are an important part of the ''*Copernicus plan*' of the European Commission, and its free and open data policy has made it possible to provide full daily coverage of 10—30 m satellite imagery around the world [40].

In addition to the privacy infringement problem caused by the enhancement of spatial resolution in the traditional sense, intelligent remote sensing satellites can provide information to a large range of people in real-time or minute-level semireal time. Thus, the resulting privacy protection issues for remote sensing data are more prominent. For instance, the European Commission authorized regulations in 2020, whereby the requirements for remote identification of its collected image data are specified according to the technical characteristics of drones (open, specific, and certified categories) so as to provide more effective privacy protection services [41]. In the future, it is imperative to establish a scientific data and information hierarchical management system for specific fields, such as public welfare, commerce, and scientific research, and formulate regulations.

V. Conclusion

Due to the rapid development of technologies related to intelligent remote sensing satellites, an increasing number of remote sensing satellites with intelligent features are being launched and are operating in the earth's orbit. Space-based information service network construction is being accelerated by moving beyond the conventional remote sensing information application model. This will realize GPS-style real-time remote sensing information services for various commercial users. Meanwhile, many challenges remain regarding the formulation of intelligent remote sensing satellite standards and remote sensing information laws. On the one hand, the intelligent remote sensing satellite standards should be unified to support the deployment and overall planning of the intelligent remote sensing satellite system; On the other hand, the healthy development of intelligent remote sensing satellite system applications should be protected by complete remote sensing information utilization laws for avoiding privacy disclosure, tort, or other problems. The construction of an intelligent remote sensing satellite system has great significance for the convenient application of global remote sensing data, with the revolution of the onboard processing system as the key for future rapid development. Specifically, the onboard computation mode of single satellites may be replaced by the edge-cloud cooperation computation mode of the constellation networks. Solving the key technical problems and completing the related technical specifications and laws will provide the foundation for promoting the development of intelligent remote sensing satellites.

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