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Research on Mineral Exploration Applications Based on Remote Sensing Technology

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Abstract. Mineral resources are crucial to a country's economic development and strategic security. The complex terrain in China, such as the Qinghai-Tibet Plateau, severely restricts the efficiency of traditional exploration. Remote sensing technology, with its advantages of large-scale data acquisition and low risk, has become one of the key means for mineral exploration. This paper analyzes and summarizes the four core technologies of remote sensing in mineral exploration: remote sensing image interpretation, alteration information extraction, hyperspectral analysis, and radar detection, and their advantages and disadvantages. It also combines multiple case studies to point out the complementary value of technologies and the potential for AI integration, while also mentioning issues such as the "black box" of AI. It looks forward to the future development of AI while providing references for mineral exploration in complex terrain areas. Furthermore, it emphasizes the importance of establishing standardized multi-source data fusion frameworks to ensure consistency in geological interpretation. In addition, strengthening interdisciplinary collaboration among geologists, computer scientists, and policy makers will be key to realizing the full potential of intelligent mineral exploration.

Keywords: Remote Sensing, Mineral Exploration, Satellite

1. Introduction

Mineral resources are the material key to supporting a country's economic development and strategic security. The development of mineral resources is related to national security and the harmonious development of society in the future. However, the international situation is changing rapidly and conflicts among countries are frequent. The acquisition of mineral resources has become the focus of competition among countries. On this basis, China's demand for energy is increasing day by day. For instance, household cars and industrial power generation all require many actual resources. Relying solely on imports cannot guarantee national energy security. Meanwhile, exploring and maintaining the stable development of domestic self-produced natural energy output is a manifestation of the national energy strategy, and mineral resource exploration also plays an important role in this process.

Due to the complex and perilous terrain and diverse landforms in China, manual exploration of complex terrain areas such as the Qinghai-Xizang Plateau has greatly limited the efficiency and accuracy of traditional geological exploration due to the topographic factors. To better conduct

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mineral exploration in such areas, remote sensing technology has become an indispensable technical means in this field. Remote sensing technology, by leveraging satellite platforms and models, enables the rapid acquisition of data over a large area without the need for personnel to conduct in-depth exploration in complex regions. This not only significantly enhances the efficiency of exploration but also helps practitioners avoid risks, and the data becomes more coherent [1].

Over the past two decades, with the emergence of multi-source satellite data such as TM/ETM+, OLI, GF-5, Hyperion, and the innovation of data processing methods, remote sensing technology has gradually evolved from the early qualitative extraction of alteration information to a quantitative prediction system integrating spectral analysis, machine learning, and multimodal reasoning. It provides key technical support for the exploration of deep-buried and concealed ore deposits. Among the traditional remote sensing alteration extraction methods, the Crosta algorithm and its improved version (iCrosta) have demonstrated significant value in mineral prediction in high-cold mountainous areas. Huang Lishan et al. focused on the high-altitude area of the West Kunlun Mountains in Xinjiang. Based on TM/ETM+/OLI multi-source data, they successfully enhanced the anomalies of iron staining and hydroxyl alteration by optimizing the band combination of the iCrosta method. Combined with the evidence weight model, they delineated 24 potential prospecting areas. Through ground verification, they discovered the lead-zinc mineralization point in the Black Mountain. The effectiveness of multi-source data fusion in complex terrain areas has been confirmed [2]. Meanwhile, the application of hyperspectral satellites has further promoted the refined identification of altered minerals. The team from the Chengdu Center of the China Geological Survey utilized GF-5 hyperspectral data and adopted the technical route of "spatial domain statistical band removal + decision tree classification + hybrid tuned matching filtering" in the Zule - Manla area of Xizang. Eight kinds of altered minerals related to porphyry mineralization, such as sodium mica and altenite, were accurately identified, providing microscopic mineralogical basis for the prediction of shallow hydrothermal deposits [3]. It can be seen from the examples that remote sensing technology is widely applied in mineral exploration, not restricted by mineral types and terrain issues, and can provide long-term support.

This paper analyzes different methods and applications of remote sensing technology in mineral exploration, such as traditional spectral modification extraction algorithms and hyperspectral mineral identification technology. From machine learning classification models to multimodal intelligent reasoning frameworks, combined with typical cases from multiple regions, it dissects the applicable scenarios and accuracy differences of different technical routes, and looks forward to the future development direction of domestic satellite mineral exploration. To explore the possibility of the combined development of satellite monitoring and artificial intelligence, and to provide theoretical and technical references for the efficient exploration of mineral resources in complex terrain areas.

2. Methods

Mineral resources are the material basis necessary for the development of human civilization. The research on the location of mineral deposits, the identification of mineralized zones, the estimation of resource reserves, and the analysis of mineralization laws is an important branch of mineral resource exploration. Combining remote sensing technology with mineral resource exploration technology can not only quickly obtain abnormal information on mineralization and dynamically monitor the status of resource development when detecting the distribution characteristics of mineral resources on a large scale, but also enable it. At present, the mainstream mineral exploration

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technologies include remote sensing image interpretation, alteration information extraction, hyperspectral remote sensing analysis, radar remote sensing detection, etc.

2.1. Remote sensing image interpretation

Remote sensing image interpretation is a technique mainly that analyzes the texture, shape, tone and other features of the visible light band remote sensing image spectrum. The texture reflects the degree of rock weathering and the differences in mineral particles, the shape reveals the different geometric forms of faults, folds and other structures, and the tone shows different lithological components. Finally, it combines geological knowledge to identify mineralized anomaly areas. Traditional methods rely on manual visual interpretation, which requires researchers to have a large amount of knowledge reserves and conduct manual comparisons of mineral characteristics. However, modern technology combines computer automatic classification, deep learning, and self-comparison to improve efficiency [4]. Among them, Principal Component Analysis (PCA) and the Optimal Index Method (OIF) are the most crucial techniques for enhancing the accuracy of extracting structural lines and lithological distributions. PCA can compress multi-band data into uncorrelated principal components through orthogonal transformation, effectively enhancing the contrast of construction information. The OIF, on the other hand, selects the band combination that best distinguishes lithology by calculating the information content and redundancy of the band combination. In the research on the inversion of chlorophyll content in wheat leaves, the combination of 760, 1860, and 1970 nm bands selected by the OIFC (OIF combined with correlation coefficient) method constructed a prediction model with a determination coefficient of 0.827, verifying the effectiveness of OIF in spectral feature extraction. In addition, Li Yansheng et al. proposed an interpretation paradigm that coupled knowledge graphs with deep learning, further integrating the dimensionality reduction advantage of PCA and the band optimization capability of OIF, achieving an overall accuracy of 83.62% in the lithology classification task [5].

2.2. Alteration information extraction

Alteration information extraction technology is a key approach based on multispectral/hyperspectral remote sensing technology to identify alteration minerals related to mineralization, such as hydroxyl and iron-staining minerals. Its core lies in inverting the hydrothermal alteration process and spatial distribution through spectral feature differences and analyzing the absorption or reflection characteristics of minerals in specific bands. Subsequently, the reflectance ratio of a specific band combination is calculated, or the hyperspectral data is decomposed at multiple scales and combined with weighted Spectral Angle Mapping (SAM) to achieve high-precision extraction of alteration information [6]. However, due to the limitations of the data's ability to identify actual minerals, it is often restricted by environmental conditions. Therefore, for the complex geological environment at high altitudes, the iCrosta algorithm, as an improved version of the traditional Crosta algorithm, performs outstandingly. This method, through principal component analysis and band combination optimization, effectively extracted iron staining and hydroxyl alteration information in mineral exploration in the West Kunlun region. Combined with geochemical data, it delineated the prospecting target area, providing technical support for deep mineralization prediction on the northwest margin of the Qinghai-Xizang Plateau [2].

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2.3. Hyperspectral remote sensing analysis

Hyperspectral remote sensing technology is a remote sensing method that achieves precise identification of ground objects by obtaining continuous narrow-band spectral data (usually containing hundreds of bands). Its core lies in utilizing the spectral feature differences of ground objects within a specific wavelength range, combined with spectral library comparison and algorithm optimization, to achieve precise interpretation of mineral composition. The number of wavelength bands that ordinary remote sensing can measure is limited. Hyperspectral remote sensing can measure continuous narrow wavelength bands. By using the envelope line elimination method to eliminate the spectral background, and finally comparing with standard mineral spectral libraries such as the USGS library, the mineral mapping is ultimately achieved [7]. Moreover, the optimization of the classification algorithm has significantly improved the accuracy of mineral identification. For instance, in the hyperspectral scanning study of the core at Chengmenshan Copper Mine, a method combining Random Forest (RF) and Support Vector Machine (SVM) was adopted. By extracting the spectral characteristic parameters of minerals such as montmorillonite and kaolinite, the fine vertical alteration zonation of the borehole was achieved, with an overall classification accuracy of 89.43% [8].

2.4. Radar remote sensing detection

Radar remote sensing detection technology is an active remote sensing method based on the microwave band. It acquires the backscattering characteristics of surface targets through full-polarization Synthetic Aperture Radar (SAR) to achieve high-precision identification of geological structures, surface deformations and mineral resources. This technology analyzes the geometric structure and dielectric properties of ground objects by emitting multi-polarized microwave signals (such as HH, HV, VH, and VV polarization combinations), and utilizes the phase and amplitude differences of different polarization channels. It is particularly outstanding in the interpretation of concealed structures, landslide monitoring, and the exploration of salt deposits. Radar can penetrate clouds and vegetation, and different substances have different abilities to reflect microwaves. Radar remote sensing does not rely on sunlight and is not affected by the alternations of day and night. It can still work stably in bad weather, making up for the limitations of optical remote sensing. For instance, in the northwest margin of the Qaidam Basin, the collaborative processing of ETM multispectral and SAR data enhanced the spectral response of salt minerals through band combination transformation, delineating four salt mine prediction areas. The results are highly consistent with the modern Salt Lake sedimentary belts and mining areas. However, SAR technology still faces the challenges of scattering interference and polarization noise. To address this issue, polarization noise suppression methods significantly enhance data quality by improving polarization similarity measures and deep learning models. For instance, the target enhancement method based on Huynen decomposition and polarization azimuth zeroing effectively eliminates the influence of random vector scattering and speckle noise, achieving consistent optimization of polarization characteristics in the same region in the full-polarimetric SAR measured data [9].

3. Application analysis

Remote sensing data in mineral resource exploration is not restricted by terrain or mineral types. Through the application of various algorithms and models and in combination with technical libraries, the accuracy and breadth of mineral resource identification can be enhanced.

The field verification showed a coincidence rate of 85%. The research finds that the 843-band combination can effectively distinguish magnetite from the surrounding rock. Meanwhile, the PCA transformation enhances the spatial distribution characteristics of the fault structure. However, during the fusion process of research data, due to the significant difference between hyperspectral and high spatial resolution, details are lost, and spectral distortion occurs, resulting in a decline in fusion accuracy. Subsequent research on related issues should be focused on to maintain the balance of data between the two sides and keep the resolution relatively consistent, which is conducive to the accurate fusion of data [10].

Bai Longyang et al. attempted to remove the band noise of hyperspectral technology by using spatial domain statistics to retain more spectral details, distinguish vegetation coverage areas, and apply hybrid tuned matched filtering to different areas respectively. However, they still could not avoid the impact on recognition accuracy caused by vegetation coverage such as shrubs. At the same time, the new method lacked sufficient verification numbers and had few experiments. It lacks universality and universality. In the future, more field verification points need to be combined, and tests should not only be concentrated in mineralized areas [11].

Dai Keren et al. distinguished the landslide area from the rest by using the C-band full polarization data of the GF-3 satellite and conducting polarization decomposition to extract the features of the scattered surface. Meanwhile, this technology can identify the specific location of the area where landslides are triggered by earthquakes by comparing data from different regions before and after the earthquake. However, relying solely on single terrain data before and after an earthquake makes it difficult to capture the process now when an earthquake triggers a landslide, and there are certain data limitations [12].

4. Discussion

4.1. The applicable scenarios and complementary relationships of different remote sensing image technologies

The visual interpretation of remote sensing images and the conventional spectral index analysis of alteration information rely on the basic interpretation and extraction methods based on professional experience. It requires the intervention of geological remote sensing professionals to complete the interpretation of ground objects and the interpretation of mineral spectral features. Although the efficiency is relatively low and it is difficult to handle ultra-large-scale data, as the foundation of technical application, it is suitable for complex ground object scenarios and has the most universal application scope. It is the benchmark for the verification of intelligent technologies.

Model-driven intelligent analysis methods such as alteration information extraction and hyperspectral matching require the construction of complex models and extensive sample training before classification. After training, the recognition accuracy of hyperspectral minerals in specific scenarios such as shallow surfaces is significantly improved. However, over-reliance on training data can easily lead to mistakes such as misjudging the alteration spectra of vegetation coverage areas as the background, and they are not adapted to the complex changes in terrain. This leads to a lack of universality in practical engineering applications.

The cross-integration of remote sensing image interpretation, alteration information extraction and radar technology has become the key path to break through the single technical bottleneck: the combination of hyperspectral fine spectral recognition and radar's all-weather penetration vegetation monitoring can make up for the blind spot of alteration information extraction in optical remote sensing in covered areas such as densely vegetated regions. This multi-technology integrated

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analysis, through the multi-dimensional correlation of spectral–radar scattering–geological features, optimizes the application deficiencies of a single technology in complex geological scenarios and provides more multi-angle technical application methods.

Furthermore, with the iteration of artificial intelligence technology, the integration of remote sensing technology and AI models is driving the transformation of geoscience information extraction from “artificial experience-driven” to “intelligent data-driven.” In recent years, deep learning models such as Transformer and U-Net have gradually emerged in tasks such as remote sensing image classification, change detection, and target recognition. However, the “black box” nature of current AI models leads to low interpretability in their decision-making processes, making them difficult to be applied in practice. For instance, in SAR image target recognition, although deep learning models can achieve a classification accuracy of 92%, they are difficult to explain the mapping relationship between scattering features and ground object types. This remains challenging in scenarios that require mechanism verification, such as landslide monitoring [13].

4.2. Future development trends and technological integration

The integration of remote sensing technology and AI models is driving the processing of geoscience information to leap from “single-modal interpretation” to “multi-dimensional intelligent decision-making.” However, the insufficient depth of multi-source data fusion, the limited ability to recognize weak features, and the need to improve the accuracy of dynamic prediction remain the core challenges. Multi-sensor data fusion can significantly improve the interpretation accuracy of complex scenes by integrating complementary information from different observation perspectives. For instance, the collaboration of optical and SAR data can break through the limitations of cloud cover and achieve continuous monitoring in cloudy and rainy areas. In 2024, a research team proposed a 3D U-Net model that combined Sentinel-1 SAR with Landsat optical data through a multi-stage feature fusion module, achieving an overall accuracy of 94.5% in crop classification, which was over 15% higher than that of a single sensor. The introduction of temperature data further enhances the coupling analysis capability of terrain and thermal anomalies. In 2025, the low-resolution filling–super-resolution reconstruction (LFSR) framework proposed by Wu Penghai’s team integrates thermal infrared and meteorological model data to generate all-weather surface temperature information, with an error of less than 2°C in regional climate change research [14].

In addition, remote sensing identification of mineral resources also faces multiple challenges such as high spectral similarity and strong background interference. The application of automatic feature learning has significantly enhanced the ability to extract weak signals. For instance, the Mineral-ResNet model proposed in 2023, which combines residual connection with 1D-CNN architecture, achieved an overall mineral classification accuracy of 92.16% in the AVIRIS data of the Cuprite mining area, and improved the recognition rate of weakly absorbing characteristic minerals such as kaolinite and montmorillonite by more than 30% [15].

Finally, it is important to promote the technological evolution from “interpretation to prediction” to achieve dynamic spatio-temporal monitoring of resources. Remote sensing technology is transforming from static interpretation to dynamic prediction, revealing the evolution laws of resources through time series analysis and spatio-temporal modeling. In the future, it is necessary to develop alignment technology networks based on the physical property differences of different sensor data, and at the same time introduce new AI tools for deep learning to enhance interpretability. Under the condition of meeting requirements, lightweight processing should be carried out to promote the development of model compression and edge computing technologies.

5. Conclusion

This paper focuses on the study of various new technologies and methods that combine remote sensing technology with mineral resource exploration and their application in actual conditions. This paper analyzes four commonly used and widely applied new technologies, including remote sensing image interpretation, alteration information extraction, hyperspectral remote sensing analysis, and radar remote sensing detection. At the same time, it lists their application examples in domestic mineral exploration. Overall, remote sensing technology has overcome the problems of traditional surveying, which requires actual human investigation and a certain amount of knowledge reserves. It integrates functions such as scanning and analyzing different minerals, offering greater efficiency advantages. Moreover, remote sensing technology is connected to satellites, and its real-time update feature makes it more convenient to conduct overall resource management and provides more comprehensive information on mineral resources. Finally, this paper provides development suggestions for the shortcomings of different technologies and briefly describes the main trends in the future development of exploration technologies.

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