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Article

Application of Multi-Source Remote Sensing Data and Lidar Data Fusion Technology in Agricultural Monitoring

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Abstract: The fusion technology of multiple and LiDAR data has important value in agricultural monitoring process, which can contribute to the accuracy of crop identification, real-time monitoring of crop growth status, and evaluation of advanced land resource characteristics. Due to the large-scale coverage and complex spectral features of remote sensing images, they have the potential to identify vegetation and soil characteristics; And LiDAR images have precise spatial structural characteristics, such as tree crown height, ground morphology, etc., which can complement the latter in structural and informational spaces, filling the limitations of single source data acquisition in representation. Of course, having great technological potential does not necessarily mean that it can be fully realized. In fact, it also faces some challenges, such as mismatched temporal spatial resolution, cumbersome data acquisition and processing processes, high development costs for hardware facilities and algorithm software, etc., all of which hinder the effectiveness and depth of the development of this technology. This article mainly starts from the agricultural and forestry scenarios, explores suitable integration development paths and strategies based on their existing problems, in order to enhance the practical value and intelligence level of agricultural remote sensing data integration, promote the intelligent and refined development of agriculture, and provide technical support for its development.

Keywords: remote sensing data; LiDAR; data fusion; agricultural monitoring

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1. Introduction

Due to the continuous promotion of policies related to agricultural technology such as precision agriculture and digital rural areas, traditional farmland monitoring methods are no longer able to meet the needs of effective and refined management. The large-scale coverage and non-contact collection capabilities of remote sensing and LiDAR technology have been widely applied in many agricultural detection systems. Especially LiDAR technology can obtain high-resolution 3D images, which can record key factors such as terrain undulation and vegetation structure, which is essential for obtaining structural support for agricultural information. Integrating remote sensing optical information and LiDAR spatial 3D data into land application research and agricultural management can achieve comprehensive information supplementation in multiple aspects such as distinguishing regions, monitoring crop conditions, and evaluating farmland quality, greatly improving the efficiency and response rate of agricultural information monitoring. Although this kind of technical framework has a good development prospect, there are still some problems in the practical application process, such as inconsistent resolution, difficulty in model matching, and high cost. This article will discuss key issues based on the application of existing fusion technologies, and explore possible solutions to provide theoretical basis and technical support for the intelligent development of agricultural monitoring [1].

2. Overview of Multi Source Remote Sensing Data and Lidar Data Fusion Technology

Remote sensing technology is based on the perception of surface radiation reflection characteristics, making it of great practical value in the field of agricultural monitoring. Optical, multispectral, hyperspectral, radar and other remote sensing data have strong diversity and wide spatiotemporal coverage information collection capabilities, which can provide comprehensive surface observation information. The LiDAR technology for constructing high-density 3D point cloud data based on the principle of active laser ranging has significant characteristics of high accuracy and rich structural information. Especially adept at collecting structural information such as terrain fluctuations and plant canopy height. By combining multiple remote sensing data and LiDAR data, spectral based structural attributes can be achieved. The spectral attributes of both can be supplemented with multidimensionality and combined with two-dimensional and three-dimensional data. This strategy has high compatibility and accuracy in complex agricultural environments, and can be applied to many scenarios, such as crop classification, growth assessment, and farmland classification, achieving the trend of intelligent and refined agricultural monitoring. In terms of data fusion, current methods are gradually transitioning from traditional stacking to intelligent methods such as deep learning and multimodal construction [2].

3. Application of Fusion Technology between Source Remote Sensing Data and Lidar Data

3.1. Improve the Spatial Recognition Accuracy of Crop Classification

As a core component of agricultural remote sensing, crop classification suffers from low interpretation resolution and spectral confusion in traditional optical remote sensing data, which cannot accurately distinguish field boundaries and crop information. And LiDAR data compensates for the height information and structural properties of ground objects, greatly improving the classification model's ability by integrating two-dimensional spectral features and three-dimensional spatial information. The use of LiDAR point data can extract information such as plant height and canopy roughness, which, combined with vegetation indices (such as NDVI) in optical remote sensing images, form a feature space that enhances the responsiveness to various crops. Common fusion classifiers include Random Forest (RF), Support Vector Machine (SVM), etc. By optimizing feature weight allocation, classification accuracy can also be effectively improved. Learning feature weights can improve classification accuracy. In the process of fusion modeling, the following feature expressions can be used to parameterize the input data:

$$F = \alpha \cdot NDVI + \beta \cdot H_C + r \cdot \sigma_C \tag{1}$$

Among them,NDVI To normalize the vegetation index,H_CFor canopy height,σ_CFor the roughness of the canopy surface,α, β, rFor feature weight coefficients. This type of fusion strategy can effectively improve the accuracy and stability of spatial recognition [3].

3.2. Realize Dynamic Monitoring of Crop Growth Status

In order to monitor crop growth in a timely manner, it is necessary to have a deep understanding of the dynamic characteristics of crop spectra and structures over time. Remote sensing data can be used to continuously extract parameters such as vegetation index (NDVI) and enhanced vegetation index (EVI) to reflect changes in crop growth. LiDAR data is used to reflect the structural characteristics, growth status, and dynamic changes in biomass of vegetation by measuring canopy height and point cloud density. By combining these two types of data, continuous tracking of crop growth processes can be achieved at both temporal and spatial scales, which is beneficial for improving the detection ability of specific issues, such as insect hazards and irrigation effectiveness detection. In the temporal evaluation model constructed based on fusion features, the commonly used crop growth functions are as follows:

$$\mathrm{G(t)} = \mathrm{NDVI(t)} \times \mathrm{H_C(t)} \quad (2)$$

Among them,G(t)For the growth index of crops at time t,NDVI(t)For the vegetation index at that moment, $\mathrm{H_c}$(t)The height of the canopy. This function comprehensively considers spectral activity and structural changes, and has good characterization ability for crop growth trends at different growth stages, supporting continuous monitoring and intelligent warning at the field scale [4].

3.3. Comprehensive Evaluation of Supporting the Quality of Arable Land Resources

The evaluation of cultivated land quality is a factor that affects the efficiency of cultivated land, including soil layer characteristics, topography, and vegetation density. Remote sensing images contain optical information reflecting crops such as surface temperature, soil moisture content, and vegetation coverage, which can characterize agricultural land types, geomorphic features, and usage intensity. LiDAR can accurately detect terrain undulations, changes in terrain, slopes, and orientations, providing reliable information support for extracting risk indicators of soil erosion and farmland suitability. By integrating spectral and structural information, it is used to evaluate the output level and degradation degree of cultivated land. In multivariate fusion models, the comprehensive evaluation function of cultivated land quality is often used:

$$\mathrm{Q} = \mathrm{w_1} \cdot \mathrm{NDVI} + \mathrm{w_2} \cdot \mathrm{S_m} + \mathrm{w_3} \cdot \mathrm{Slope} \quad (3)$$

Among them,QThe Farmland Quality Index,NDVIFor vegetation coverage, $\mathrm{S_m}$For soil moisture index,SLopeFor slope factor, $\mathrm{w_1}, \mathrm{w_2}, \mathrm{w_3}$For weight coefficients. This model combines planar and three-dimensional features to effectively support farmland classification, priority protection area division, and precise policy implementation, providing high-precision data basis for agricultural resource management [5].

4. Problems in the Application of Fusion Technology in Agricultural Monitoring

4.1. Difficulty in Matching Spatiotemporal Resolution of Data Sources

There are significant differences in temporal and spatial resolution between remote sensing and LiDAR data, making it difficult to achieve coordination and consistency between the data. On the one hand, although remote sensing images have the advantage of efficient monitoring of ground conditions, their spatial accuracy is insufficient, making it difficult to depict the details of farmland structures; On the one hand, LiDAR data can provide high-precision three-dimensional structural information, but its update time is relatively slow, there are limitations in coverage, and it cannot be observed continuously at any time. And these two types of data are usually obtained at different times, resulting in differences in ground conditions and increasing the difficulty of comparing and analyzing them at the same time. In addition, both types of data also involve multiple coordinate systems, projection methods, and data formats, which increase the difficulty of data processing and can easily lead to problems such as data alignment errors and feature shifts. Accuracy of agricultural monitoring results.

4.2. Information Redundancy and Difficulty in Collaborative Modeling

In the process of integrating remote sensing images and LiDAR data, due to the significant differences in the types and forms of remote sensing images and LiDAR data, there may be issues such as duplicate information and model construction. Remote sensing data mainly provides spectral reflectance information in multiple bands, while LiDAR data is mainly represented in the form of three-dimensional points, including structural characteristics such as height and density. This heterogeneity leads to a large amount of redundant or irrelevant information in the dimensions, which affects the extraction of correlation and the analysis of identifying important information. The more dimensions there are, the higher the complexity of the relevant dimensions, resulting in greater computational complexity and difficulty in parameter optimization. Meanwhile, remote sensing and LiDAR have different ways of expressing the same object, and the lack of a unified data organization structure and interface specification makes it difficult to support flexible model design for different data sources. During the training process, convergence instability or accuracy fluctuations are prone to occur, which affects the practicality and reliability of agricultural monitoring.

4.3. High Cost Investment and Limited Application Promotion

Due to the high economic and technological barriers in practical applications of multi-source remote sensing and LiDAR fusion technology, the widespread use of multi-source remote sensing and LiDAR combination technology in the agricultural field is limited. High quality LiDAR products are expensive, and data collection requires specialized service platforms and technical personnel, with a significant cost per task. Although some remote sensing data is publicly available, high-resolution and multi temporal images are usually paid resources. For farmers, the burden is heavier. The fusion processing process requires high hardware performance and software tools, involving modeling, image processing, and multiple collaborative algorithms, and requires high professional technical capabilities. However, due to the lack of relevant technological support or database construction conditions in most rural infrastructure, it is difficult to achieve stable and efficient integration technology processing, and it is difficult to popularize and apply this technology (As shown in Figure 1).

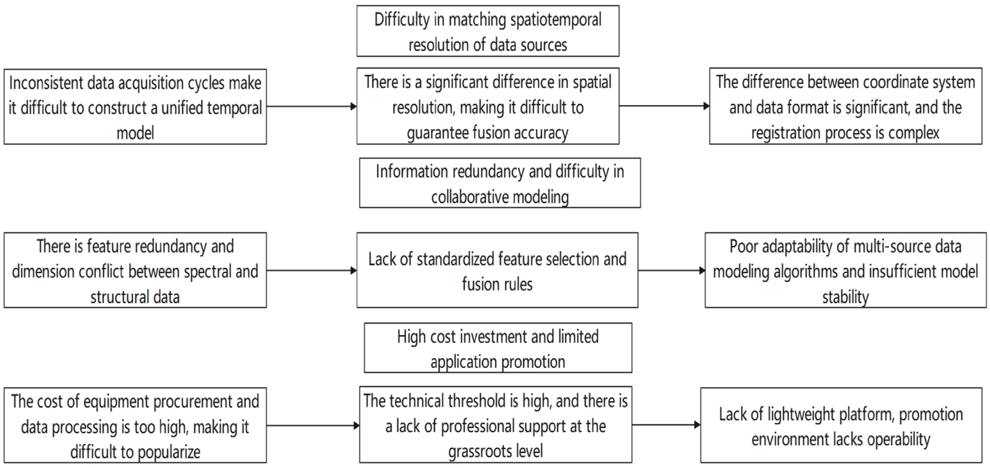

Figure 1. Problems in the Application of Fusion Technology in Agricultural Monitoring.

5. Optimization Strategies for the Application of Fusion Technology in Agricultural Monitoring

5.1. Establish a Multi-Scale Registration and Interpolation Algorithm System

The heterogeneity of multi-source remote sensing and LiDAR data at the spatiotemporal scale requires the application of scientific methods for registration and interpolation algorithms to present them uniformly. The multi-scale registration method can effectively improve the accuracy of spatial positioning by using region adaptive registration techniques and feature matching algorithms based on the resolution difference between remote sensing images and point cloud data. In terms of time dimension, a temporal interpolation model can be constructed, which can be processed using methods such as spline interpolation, linear regression, or Kalman filtering. Joint processing of data collected at different times to re estimate the numerical information of key observation points. For data with uneven spatial density, the mutation function and Kriging interpolation algorithm can be used to complete spatial information and fill in the blank information in sparse areas. By combining operations such as multi-source projection conversion, coordinate reconstruction, and data resampling, a multi-scale collaborative processing flow is constructed to improve the stability and consistency of data fusion.

The research team will integrate unmanned aerial vehicle LiDAR point clouds with Sentinel-2 multispectral remote sensing images to conduct collaborative application research in major corn producing areas in western Jilin. Simultaneously applying spline interpolation of time-series NDVI data to fill in remote sensing gaps, further utilizing high-precision registration and interpolation completion techniques to improve data consistency and integrity, achieving precise monitoring of the three-dimensional structure of corn fields and dynamic observation of corn growth status. By adopting a strategy of multi-scale registration and interpolation, the recognition accuracy of crops is improved by 12% compared to single data, indicating the effectiveness and feasibility of fusion technology.

5.2. Constructing a Multimodal Deep Fusion Feature Model

Multi modal information multi-scale fusion utilizes neural network structure to deeply fuse spectral and 3D structural information. Through a dual channel convolutional neural network (Dual BranchCNN), feature vectors of remote sensing data images and LiDAR point clouds are extracted separately. Information fusion is carried out through feature connections and interactions. In this process, a multi-scale feature extraction branch is introduced to better preserve the spatial details and semantic features of crops. This model can combine supervised learning and transfer learning methods to enhance its adaptability and generalization performance to small sample regions. For multi temporal data, dynamic features are constructed using temporal neural networks (such as LSTM) to achieve comprehensive evaluation of crop growth status structure and spectrum, thereby improving classification and prediction accuracy.

Researchers used PlantScope remote sensing images and airborne LiDAR point cloud data to construct a deep fusion scheme based on a bipartite sub residual network. Spectral information such as NDVI and red edge index were obtained from remote sensing image input, and attribute information such as canopy height and point density were fused from point cloud channels to effectively extract structural features. The channel attention module was used as the key technology of the fusion layer. Through testing, it was found that this method can achieve an overall accuracy of up to 91.2%, which is much higher than traditional feature stitching methods and also demonstrates the significant effectiveness of multi task deep fusion schemes in improving farmland remote sensing recognition capabilities.

5.3. Promote Low-Cost Platforms and Lightweight Algorithm Deployment

To achieve large-scale application of remote sensing and LiDAR data fusion technology, on the one hand, it is necessary to optimize low-cost acquisition equipment and powerful computing modes. The modular design of smaller unmanned aerial vehicles significantly reduces the assembly requirements of payloads, loading high-resolution multispectral sensors and small laser scanning devices together for high-precision data acquisition operations. In terms of algorithms, establishing a lightweight deep learning model is a necessary means. By using methods such as network pruning, weight pruning, and knowledge extraction, the model structure can be greatly simplified while maintaining its normal operation on low-power computers. Adopting an end-to-end cloud collaboration framework, edge devices are mainly responsible for preprocessing and primary inference, while the main task of the model will be pushed to the cloud for deep level fine interpretation, which can effectively reduce the burden on the terminal. A unified interface standard and automatic deployment script can achieve rapid model migration and meet the needs of various platforms, which is beneficial for other reuse within the agricultural sector and enhances the applicability and continuity of fusion technology.

The agricultural work site monitoring system based on JetsonNano edge devices developed in this article has been deployed on farmland in the southeastern region of Hebei Province. The system is equipped with payload level LiDAR modules and dual spectral cameras. The collected images and point cloud data are processed locally using the lightweight model ShuffleNet, and the land boundary map and crop coverage map of the work site are calculated. The processing time is only 1.8 seconds, and the classification accuracy can reach 90.4%. The total system cost is only about 60% of traditional methods. The system worked for two weeks and basically formed a closed loop from collection to calculation to return, indicating that the low-cost and lightweight algorithm combined with appropriate hardware costs is practical and has good market prospects.

6. Conclusion

The comprehensive utilization of multiple remote sensing and LiDAR technologies can provide us with more complete, three-dimensional, and highly accurate data support for agriculture, making it widely used in crop classification, growth monitoring, and land resource evaluation, demonstrating extremely broad development prospects. The combination of multiple technologies complements each other in terms of spatial representation and information level, fully enhancing our use of agricultural information to obtain angles and accuracy. However, there are some technical limitations to the application of this method, such as mismatched resolution, complex data processing, high technical barriers and investment costs, which have hindered the application of this technology in agriculture, rural areas and farmers. However, with the optimization of intelligent algorithms and the continuous simplification of model structures, this technology has broken through previous technological limitations and achieved more applications. The future development goal is to strengthen the establishment of standards, improve data sharing and model adaptation processes, and enable them to be applied in agricultural production management on a large scale and standardized. This will achieve intelligent, efficient, and systematic improvement of agricultural monitoring, ensuring the scientific and sustainable allocation of agricultural resources and accelerating the digital, refined, and scientific development of modern agriculture related to agriculture, rural areas, and farmers.

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