**Application of CV technology in remote sensing monitoring**

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**Abstract**:In recent years, deep learning has made remarkable achievements in the application of computer vision, and the image processing ability has made rapid progress. With the increase of remote sensing image data and with the improved the image quality, spectral and spatial resolution. Remote sensing images can fully display the detailed information of ground objects. Deep learning algorithms can be iterated through multi-layer convolutional neural networks, which can fully mine the hidden pattern information in remote sensing images, thus obtaining better interpretation effect and laying a foundation for remote sensing analysis and application. Based on the development and application of computer vision, this paper [analyses](https://fanyi.sogou.com/?keyword=analyse&fr=websearch_submit&from=en&to=zh-CHS) the application of computer vision technology in remote sensing field, summarizes the remote sensing research of computer vision in vegetation, hydrology, ecological environment and public facilities, and summarizes the typical remote sensing application results. Finally, this paper analyzes the shortcomings and development trend of computer vision in remote sensing, and looks forward to the future application of remote sensing.

**0 Introduction**

Computer Vision (CV) is a discipline that uses visual imaging systems such as computers and cameras to replace visual organs to recognize, track, measure, and process graphics [1]. Deep Learning has achieved great results in image processing applications. The ability of computer vision to perform in many simple linear tasks has reached or surpassed the level of human vision. It can be applied to image classification, segmentation, target positioning, detection and Gait recognition. The development of computer vision has also provided a breakthrough for the processing and analysis of remote sensing data. The performance of remote sensing detectors has been improved, the quality of images and the spectral and spatial resolution of images have been improved, and the ability of remote sensing images to display features and details of features has been greatly improved. The remote sensing interpretation of surface features can no longer meet the needs of current remote sensing applications. Deep learning algorithms can be iterated through multi-layer convolutional neural networks, which can fully mine the hidden pattern information in remote sensing images and obtain good interpretation effects. Remote sensing image analysis application provides the basis. Starting from the latest research results of computer vision, this paper combs the current application of computer vision technology in the field of remote sensing, and summarizes the remote sensing research of computer vision in vegetation, hydrology, ecological environment, and public facilities. The application results are summarized, and the results and experience are accumulated for the application and mining of remote sensing data. Finally, this article analyzes the application deficiencies and development trends of computer vision in the field of remote sensing, and prospects for future remote sensing applications.

1. **Application of computer vision**

This chapter provides an overview of the typical application areas of computer vision, including image object recognition, classification, image segmentation, target monitoring and tracking, and gait recognition. A brief summary of the applied deep learning algorithms is made. The mathematical mechanisms of some algorithms are too complex and redundant, so they are not the focus of the article.

**1.1 Image classification**

Image classification is to identify the category of the object in the image. Traditional image classification relies on manual design and manual feature extraction to determine the object category. The ILSVRC competition champion was obtained from the AlexNet network model. The image classification result is an order of magnitude more accurate than traditional methods. Object classification under deep learning has become a popular research topic favored by scholars. Subsequently, different scholars improved the neural network structure and extended the depth of the neural network structure.Residual neural network (Deep Residual Network, ResNet) realizes the layer jump connection, and trains the objective function network by training the residual function. Densely Connected Convolutional Networks (DenseNet) alleviate the problem of gradient disappearance, enhance feature propagation, and reduce the amount of parameters . Of course, the improvement of classification methods is also accompanied by the expansion of data sets. Many scholars have studied new classification methods, such as scene-based classification.

**1.2 Image segmentation**

The study of image segmentation has been an important basic-level research work since the birth of computer vision technology. How to segment the target feature from the image is of great significance for compressing data and carrying out subsequent work. Traditional image segmentation methods mainly use SLIC, HOG, SUR and other features to interpret images through manual design. Although this method runs faster and more efficient, it can only learn shallow features, and the segmentation accuracy is low. The semantic segmentation method proposed by deep learning introduces semantic information to assist segmentation to improve segmentation accuracy. With the development of semantic segmentation, instance segmentation is proposed. In 2018, Kirillov et al. proposed panoramic segmentation, which further developed the research on semantic segmentation, and panoramic segmentation was used to generate a unified, global segmented image . Assign a label and an ID to a pixel in the image, which improves the efficiency and accuracy of segmentation.

**1.3 Object recognition**

Object recognition, that is, locate and find out the position of the object in the image. Recognition is one of the most basic tasks of computer vision, and it is the basis of advanced tasks such as detection and tracking. Object recognition has gone through the traditional sliding window to the present object recognition detection based on deep learning. Among the framework models proposed by many scholars, object recognition and detection algorithms based on deep learning can be roughly divided into three categories: based on region candidate models, based on regression models, and based on attention mechanism models [2], the main current main object recognition algorithm models are summarized As shown in Table 1.

**Table1 Object Recognition Algorithm Model**

|  |  |  |
| --- | --- | --- |
| Algorithm type | Main algorithm | Brief description of algorithm principle |
| Based on the regioncandidate model | SPPNet3]，Fast R-CNN[4]，MASK R-CNN[5]等 | first select the region of interest, and then extract and distinguish the type according to the features of the region of interest |
| Based on the regression model | YOLO[6], RetinaNet[7] | Directly locate the regression frame and its category |
| Attention-based model | AttentionNet[8] | Locate the border of the object by aggregating weak monitoring information |

**1.4 Target detection and tracking**

Monitor the target feature and its movement trend in the target image or video. Currently, the commonly used framework is based on CNN-based sliding window detection. These methods usually have a certain detection accuracy, but there are some shortcomings of fuzzy target positioning and inaccurate positioning. Therefore, experts and scholars have proposed improved methods, most of which use deep learning for CNN variants to apply to target detection. Propose a new pooling layer and learning strategy [14-15], and other deep models are applied to target detection, such as a saliency mechanism-based target positioning method combined with DBN to achieve remote target detection in remote sensing images [16], using a fusion deep learning method Etc. [17].

Target tracking is the monitoring of the dynamic and continuous changes of target features on the video. The current method of correlation filtering and deep learning is target detection. The VOT series of competitions represent the latest research on target tracking, summarized in Table 2.

**Table2 VOT series champion**

|  |  |  |
| --- | --- | --- |
| Year | Team | Brief introduction of algorithm |
| 2016 | Danelljan M, Hager, Gu | Cot tracking method improves performance in srdcf [18] |
| 2017 | The Lu Huchuan team of Dalian University of Technology | Let CNN focus on the regression of specific regions, and correlation filtering focus on the global regression and combination [19] |
| 2018 | Xu T，Feng Z | Fadcf algorithm, adaptive spatial feature selection and temporal consistency constraint [20] |

**1.5 Gait recognition**

With the development of biotechnology and deep learning, computer vision has a bright application prospect in the field of gait recognition. Everyone has different walking postures and amplitudes, which creates the specificity of people's motion states. Gait recognition models are mainly divided into discriminant models and generative models. The main results are shown in Table 3. The GaitSet algorithm model proposed by the latest research of Fudan University [26] regards gait as a collection of independent frames, abandons traditional thinking, and improves practicality and flexibility.

|  |  |  |
| --- | --- | --- |
| Gait recognition model | Feature selection and transformation | Brief introduction of principle |
| Discriminant model | gait energy map [21], key points of human posture [22], gait sequence similarity [23] | Based on the gait features, it can be distinguished directly |
| The generative model | gait generation countermeasure network [24], transforms gait features into another state based on multi-layer self coding [25] | The gait features are transformed to another state and then matched or extracted |

1. **Application status of CV technology in RS field**

Computer vision has been applied in the field of remote sensing for a long time and has a wide range. This chapter mainly introduces the current situation and shortcomings of remote sensing applications of computer vision under deep learning, including vegetation, water conservancy, environment, and public facilities.The specific application process is shown in Figure 1.

**Fig.1 Application of CV technology in RS field**

 

* 1. **Application in vegetation remote sensing**

**2.1.1 Plant identification and classification**

The traditional remote sensing image plant identification and classification work is mainly carried out according to the modular process of remote sensing image preprocessing, plant feature selection and extraction, classification recognition, and post-classification processing. This process is not only complicated and cumbersome, but also most traditional algorithm models (random forest, support vector machine, etc.) lack parameters and are not highly versatile. The deep learning algorithm can take the simple and direct plant spectrum, spatial distribution, phenological period and other feature information in optical and radar images as input, and amplify the highly relevant features in the hidden layer of the model, suppress secondary information, and finally directly Output classification results to achieve end-to-end training. This parallel method of feature selection and classification tasks simplifies the process of crop identification and classification. For different remote sensing research areas, image data changes can be transferred to other tasks through adjustment of network parameters.
 Plant identification and classification tasks mainly include the classification of crops, the identification and processing of weeds, the census and monitoring of forest resources, the monitoring of illegal farming behavior, etc. It is the basic work of plant remote sensing application analysis. Most of the deep learning models currently applied to plant recognition and classification are CNN, RNN, LSTM and their variant models RefineNet, etc. [27-33]. The introduction of these models in remote sensing applications to identify and classify plants provides reasonable suggestions for the decision-making management of government departments such as agriculture and forestry.
**2.1.2 Monitoring of pests and diseases**

 The prevention and monitoring of pests and diseases is mainly based on different remote sensing data to analyze the spectral response characteristics of pest stress, select the sensitivity spectrum characteristics (blue, red, yellow edges and their derivatives, vegetation index, etc.), carry out algorithm modeling, and distinguish between pests and diseases. The category and the severity of plant damage to achieve the purpose of pest prevention and monitoring. At present, computer vision technology is mostly used in aerial remote sensing photos. Large-scale image applications such as satellite observations also rely on traditional independent selection of spectral texture and other features for identification and monitoring. The current research mainly focuses on plants with large planting areas and typical disease mechanisms such as rice, wheat, tomato, tobacco, and pine. The source of the picture data is self-collected.

In the monitoring of pests and diseases, the application of deep learning algorithms such as CNN, RNN, and GAN is more common [33-38]. Compared with traditional methods, it has higher accuracy and recognition speed, but it also requires longer training time. Although the current remote sensing of pest monitoring has high accuracy on single and a few pest characteristics, the time resolution of the image has poor performance in the overall occurrence and development of pests and diseases, resulting in plant pests and diseases that are only detected after they have developed. Lead to poor preventability. With the further development of drone remote sensing and computer vision, dynamic pest monitoring will be an important direction for future research.

**2.1.3 Crop yield estimation**

The current main process of crop yield estimation by remote sensing is crop area estimation, which is based on vegetation index and yield data over the years to conduct dynamic growth monitoring, and build a remote sensing yield estimation model. Currently, the two common types of yield estimation models are parametric physical models, which are based on statistical models. Deep learning is introduced into the crop yield model, which can directly extract high-level semantic information from the original features of remote sensing images. The remote sensing images of the past years are used as the input layer, and the crop yield can be used as the output layer to construct a time series. The selection and adjustment of parameters can perceive the relationship between crop yield and growth environment, and finally achieve accurate yield estimation.

At present, the research on crop yield estimation based on deep learning mainly uses CNN, RBM, and a mixture of multiple models [39-41]. Deep learning solves the contradictory relationship between traditional statistical models and the complex environment, and reduces the amount of manual actual sampling. It is inconvenient, but the current crop deep learning model lacks the description and expression of the growth mechanism and the sample database is small. The performance of the deep learning algorithm is limited. With the increase in the number of remote sensing data types, the yield estimation will be more accurate.

**2.2 Application in hydrological remote sensing**

**2.2.1 Water body identification and change monitoring**

Traditional remote sensing image water body identification methods include threshold method, water body index, object-oriented method, etc. Although they have certain accuracy, these methods are not good enough in the decomposition of complex terrain and mixed pixels, and are limited by the researcher's experience. Deep learning methods, the current semantic segmentation solves the above problems, and can solve the problem of indistinguishable lakes and rivers. The main model is CNN and its deformation [42-45]. On the basis of water body identification, the surface runoff, flow velocity, and river width in remote sensing images are monitored. The semantic segmentation model divides the water body remote sensing images and compares the changes of water bodies in a certain time series to achieve the purpose of change monitoring.
**2.2.2 Flood prevention and monitoring**

The application of remote sensing in flood disasters is mainly in the dynamic monitoring of the flood range and post-flood loss assessment. Water body identification and segmentation is the basis for work development. Traditional water body identification mainly relies on water spectrum, spatial distribution and other characteristics to integrate water depth and width and other hydrological information for identification. Classic algorithms include threshold method, regional growth method, multi-band combination to form water index and so on. Deep learning can intelligently and autonomously extract the spectrum, texture and other information in the image, perform semantic extraction, and finally perform water segmentation. Common segmentation methods include U-Net, Deeplab, etc. [46-49], and perform the same in different time periods. To identify the geographical location and compare different types of features in the same area to determine the spread of flood disasters, providing a basis for rescue and disaster relief. Some scholars also use deep learning methods to monitor the water surface in real time based on the characteristics of water level, length and width of the water surface [48,49]. Although this method can be carried out around the clock, it lacks a grasp of the overall scope of flood disasters. Due to the current constraints of weather conditions and time resolution, remote sensing has not been able to find a balance between timely, accurate and overall control in flood prevention and monitoring. With the application of radar images, drone images, and computer vision With the advancement of technology, the current problems will be solved.

**2.3 Application in environmental remote sensing**

**2.3.1 Application in atmospheric environment**

Atmospheric remote sensing applications mainly include remote sensing image defogging, air pollution forecasting and monitoring, cloud image cloudiness prediction and judgment, etc. Traditional image defogging work mainly relies on image enhancement and physical model restoration. The image defogging relies on the atmospheric scattering model. The key is the transmittance and transmission rate of light in the atmosphere. Train clear images through algorithm models, obtain model parameters through multiple iterations of training, predict foggy images, calculate atmospheric transmission transmittance and transmission rate, and finally output defogging images. Common algorithms are CNN, GAN, etc. [50-51].

Air pollution forecasting and monitoring mainly rely on the concentration of harmful gas particles (PM2.5, O3, SO2, etc.), weather conditions, air quality index (AQI), etc. as indicator inputs. Application models include DBN, CNN, etc. [52-53]. Type and degree of air pollution. Different from classic forecasting methods, the deep learning model not only improves forecast accuracy, but also excavates characteristic information to find the main factors that cause air pollution, providing precise countermeasures for preventing and controlling air pollution.

The current method of monitoring and calculating satellite cloudiness cloud images is based on the ratio of the number of cloud image pixels to the total number of remote sensing image pixels, or the radiation reflectance value. Therefore, cloud detection is an important link. Cloud detection is mostly a threshold method and traditional cluster analysis algorithms, but the surface layer Cloud features have low detection accuracy. Deep learning to mine cloud features can better represent the detailed information of cloud images and obtain better interpretation results. The main application models are DELM and CNN, etc. [54-55].

**2.3.2 Application in animal protection**

The traditional methods of animal identification and protection mainly include distance method and human visual judgment method. These methods are inefficient and time-consuming. Remote sensing images under the deep learning model are used to identify and monitor rare animals and screen injured animals [57-59]. Collect rare animal images to establish a sample library, extract and classify animal features by constructing an optimized neural network, train the model to achieve optimal performance, and finally achieve automatic identification and tracking of wild animal tracks to protect animals. The current labeled data sets of wild animals are small in magnitude, and some models are not optimized for training.

The walking posture and gait characteristics of the injured animal are different from those of the normal animal. By preprocessing the animal photos, the gait energy, gait sequence and other characteristics in the image can be selected to compare the behavior database of normal and injured animals. Yes, the training model is classified, which can automatically identify and screen injured animals, and provide timely and effective treatment. Wild animals have a wide range of movement and unpredictable behaviors. There are few current studies. Some scholars have achieved certain results in livestock that are easy to control such as pigs and cattle. In the future, animal data can be added through the wearing of non-destructive sensors and drone aerial photography to achieve better recognition results.

**2.3.3 Application in geological environment**

Remote sensing of geological environment applies rock mass lithology judgment and geological entity recognition to detect natural resources such as oil and gas, metal minerals, or to predict geological disasters. The lithology of the mineral composition is complex, and the introduction of deep learning solves such problems. Through the analysis of the lithology sensitivity curve (GR, GNL, DEN, etc.) through logging, the selection of appropriate lithology parameters as input and iterative training can predict Lithology. The main models are CNN, DBN, CRBM, etc. [60-63].

In addition to geological entity recognition, some scholars also use photos to recognize them. The traditional method mainly relies on manual creation of entity text database, and the geological recognition efficiency is low. Computer vision can automatically acquire features in geological images, perform high-level semantic extraction, perform final entity recognition model training, predict bad entities through the model, perform pre-judgement detection, and predict geological disasters such as earthquakes. The current entity image data is small and the model lacks stability. Performance and accuracy need to be improved.

**2.4 Remote sensing application in infrastructure and public facilities**

**2.4.1 Traffic road**

The remote sensing traffic application mainly includes traffic conditions, pedestrian and vehicle entities, and traffic signs [63-65]. Traffic mainly relies on traffic road length and vehicle recognition and positioning system monitoring to form traffic flow, traffic volume inversion traffic conditions, under the background of unmanned driving, the application of CV technology in the transportation field is numerous and complex, and many algorithm frameworks can be applied to pedestrians. Vehicle identification. H3D, nuScenes, CamVid and other driving data sets are also emerging in endlessly. The road surface adhesion coefficient and vehicle and pedestrian monitoring are extracted through remote sensing images to realize the selection of steering wheel deflection speed. The application of traffic roads has developed rapidly, and some industrial scales have been achieved.

**2.4.2 Power inspection**

Traditional manual power inspections are time-consuming and laborious. As drones take more images of power poles, deep learning target detection algorithms can be applied to power inspections. Unlike other applications, power poles are less likely to encounter natural disasters and man-made damage, but the model training requires a similar proportion of normal damaged data, and more expansion preprocessing of damaged data (zoom, translation, color synthesis, etc.) is required. According to the regional candidate model, the regression model is trained, the mode is tested in multiple scenarios, and finally the power inspection task is completed. Commonly used models are CNN, RCNN, MASK-CNN, YOLO, etc. [66-67].

**2.4.3 Identification of pipeline defects**

Oil and gas and water pipelines are the underground guarantee for residents’ lives. Manually peeked pipelines are inefficient and potentially dangerous to workers. The feature selection extraction of pipeline disconnection, deformation, misalignment, and precipitation is to identify key objects, and then damage data through training. Certain category recognition accuracy, repair work for categories. The main models are Fast-CNN, CNN, etc. [68-70]. At present, this research is seldom, and the speed of model recognition cannot meet the demand, which has certain reference significance for municipal construction work.

1. **Discussion and outlook**

The above review summarizes the application of CV technology in the field of remote sensing monitoring. Although the deep learning algorithm takes a long time to train, it improves the accuracy of remote sensing image recognition, monitoring, and classification, and the model has strong generalization and portability. It can achieve better results in similar remote sensing projects. Part of the work can still obtain better application results through remote sensing data balancing, amplification and other operations, while saving data collection time and reducing workload.
 CV technology has achieved certain results in the field of remote sensing applications, but there are still the following shortcomings through analysis: First, deep learning models require large data sets for training and verification. Currently, most of the data sets used by scholars are self-collected and are relatively large. Small, it is difficult to achieve longitudinal comparison of algorithm models, and it is difficult to judge training results. The current sample features of remote sensing data and images need to be artificially labeled for training, and professionals are required to perform labeling work. Finally, although the current CV technology can extract remote sensing training data features, it lacks the ability to migrate and generalize data features. For example, the current use of deep learning algorithms to identify tree species on remote sensing data is mostly a single tree species, lacking the commonality of tree species characteristics, and further research is needed to determine whether it can be migrated to other tree species identification. In short, the current application scenarios of CV technology in the field of remote sensing monitoring require further improvement in the scope and depth of research content:

As far as application achievements are concerned, remote sensing data is a survey method with high integration and large monitoring range, but the current remote sensing application tasks are mostly single linear tasks, and there are few parallel complex remote sensing tasks. On the one hand, the current deep learning model is relatively complex, with numerous parameters, a long training process, and high requirements for computer hardware. At the same time, different scientific research work has different requirements for professional literacy, and the effect of integrated work is difficult to guarantee. With the development of computer vision, the ability of computers to learn autonomously has improved, the remote sensing monitoring mode and efficiency have been improved, and batches of complex remote sensing tasks have been solved.

The current research is mainly static image research, and continuous dynamic monitoring research still needs to be strengthened. How to implant deep learning models into remote sensing sensors and cameras to achieve end-to-end research results and the implementation of researchers' theoretical results is a common problem faced by scholars. For example, the construction of smart cities based on remote sensing monitoring, applying CV technology to real-time collection, collection, analysis and mining of remote sensing information on traffic roads, medical and health, and living environment, and finally achieve the purpose of assisting decision-making by government departments.

In terms of theoretical methods, the current deep learning model needs to be studied in several aspects. First of all, in terms of feature extraction, current features mainly rely on manual tags, and automatic feature extraction needs to be further developed.

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In addition, the generalization and learning capabilities of the model need to be improved. By observing the current state of things, predicting the future is more accurate. Finally, the time efficiency of the deep model needs to be improved. By simplifying the model result parameters, reducing training time is also one of the research goals of scholars.

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