Proceedings of the 4th International Conference on Materials Chemistry and Environmental Engineering
DOI: 10.54254/2755-2721/84/20240906

Improving remote sensing analysis

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Abstract. "Improving Remote Sensing Analysis" examines how remote sensing data is classified and offers various ways to improve the process's precision and effectiveness. It is emphasized how crucial remote sensing analysis is in a number of domains, including resource mapping and environmental monitoring. The strengths and weaknesses of three classification techniques—support vector machine, logistic regression, and random forest—are thoroughly examined. Furthermore, three approaches to spatial-spectral categorization are presented: pixel-based, object-based, and hybrid. These techniques successfully capture the intricate spatial and spectral properties of remote sensing data by analyzing a dataset. This discovery is important because it will improve remote sensing analysis capabilities, allowing for accurate and rapid information extraction for various applications. This essay highlights the usefulness of classifying remote sensing data and the room for improvement to improve environmental monitoring, resource mapping, and other relevant topics.

Keywords: Classification, Logistic Regression, remote sensing.

1. Introduction

The study focuses on the classification of remote sensing data. Because classification findings might influence how remote sensing data is used in the future, it is important to master some efficient classification algorithms. To overcome the problem, three classification algorithms are offered in this paper: support vector machine, logistic regression, and random forest. In addition, three alternative spatial-spectral classification approaches are investigated: the 3-stage method, a version of the 3-stage method, and spatial random forest. The purpose is to thoroughly understand remote sensing data classification and evaluate datasets through introduction. The three common classification methods will be introduced first, followed by the three spatial-spectral classification approaches. Finally, there will be the introduction of datasets and the conclusion.

2. Classical pixel-wise classification

The pixel level is a common concept in computer vision, and each pixel is processed and analyzed in order to understand the details in the image. Therefore, the color and intensity of each pixel will be taken into account during the very fine and accurate processing of the pixel level. This processing

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method is usually used for image enhancement, noise removal, and edge detection tasks. However, this kind of detail processing will have a relatively high requirement on time and computing resources and is susceptible to noise interference and sensitive to human factors. For example, in lung CT, pixel-level details need to be cut to identify and obtain the distribution and shape of lung tissue. Common pixel-level processing technology in computer vision. Usually, brightness adjustment is used to fine-tune the color of each pixel in the image, enhance the difference between pixels and remove noise, make the image cleaner by eliminating noise, scale and stretch the pixels of the image horizontally and vertically, and cut a certain part of the image to obtain key information and improve the accuracy and readability of information. Binarization converts the gray value of a pixel into a black and white color. These pixel level processing technologies can be used alone or in combination, and applying these technologies provides more possibilities for image processing. Still, it should be noted that different images have different characteristics and structures, so it chooses the appropriate necessary pixel level processing technology according to the specific image to achieve the best effect. The pixel level is relatively common in computer vision to understand the details of the image. The image analysis and processing will consider color and intensity and more processing methods. This is more demanding on time and computing resources, but different processing techniques must be used for different images to achieve the optimal choice.

3. Support Vector Machine

A Support Vector Machine is a learning algorithm for classification and regression tasks. It is effective at handling complex and high-dimensional datasets. SVMs gained popularity because of its ability to find optimal decision boundaries that maximize the margin between different classes, making accurate predictions.

The basic idea of an SVM is to transform the input data into a higher-dimensional feature space using a kernel function. It will construct a hyperplane in the transformed space that separates the data into different classes. The hyperplane means the decision boundary that maximizes the margin; in other words, it is the distance between the hyperplane and the nearest data points from each class, and it is called the support vector. SVMs aim to improve generalization and improve the ability to classify new, unseen instances by maximizing the margin.

One of the most important strengths of SVMs is their ability to handle non-linearly separable data. BSVMs implicitly map the original data into a higher-dimensional space using a kernel function, where linear separation becomes possible. In addition to its classification capability, SVMs can handle multi-class classification problems using methods such as one-vs-one and one-vs-rest. In the one-vs-one approach, SVMs are trained on pairs of classes, creating multiple binary classifiers. The final prediction is made by aggregating the results of these binary classifiers. In the one-vs-rest approach, a separate SVM is trained for each class, and the class with the highest output is considered the prediction.

Three steps make up the recommended hyper-spectral image classification method. It illustrated how it can make use of both spectral and spatial data. This method uses the nested window with the highest correlation during the initial pre-processing phase, and then it employs Pearson correlation to reconstruct the pixel data. This improves spectral signature consistency between consecutive pixels, especially in vast uniform areas with different inner-class spectra. The recovered data is subsequently dedimensionalized using Principal Component Analysis.

In the second stage, it applied a semi-supervised classification approach. The Support Vector Classifier, a subset of the Support Vector Machine, is trained. This results in a probability tensor with estimated probabilities for all classes. Due to the integration of spectral and spatial data, robust classification with few labeled pixels is possible during this phase.

During the final post-processing phase, a smoothed total variation model is applied. This step increases classification accuracy because it deletes single misclassified pixels and increases connection across spatially homogenous regions. The method stands out for its simultaneous segmentation and

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denoising using the smoothed total variation model. These guarantee both class differentiation and the enhancement of spatial homogeneity.

As the benefits of this strategy to those of other existing tactics are being compared, incorporating geographical information considerably improves accuracy clearly. The method that had been proposed uses the relationship between neighboring pixels and combines it with spectral data in order to achieve better classification accuracy with fewer labeled pixels than the alternative approaches. Pre-processing is famous for emphasizing the enhancement of spectral constancy in large homogeneous areas, and it helps when handling situations with fluctuating inner-class spectra.

Furthermore, the smoothed total variation model implementation in the post-processing step helps to refine the classification findings by efficiently removing isolated misclassifications and encouraging spatially cohesive regions.

Denoising and segmentation together make the interpretability of the classification result better. This method is good at combining spatial and spectral information. and this causes higher accuracy of the hyper-spectral picture classification with minimum labeled data and improved spatial homogeneity.

4. Logistic Regression

Logistic Regression is a statistical way to solve the problems of multi-classification tasks, which is used in predicting the result of a binary system and dividing examples into one of two classes [1]. The basic principle of Logistic Regression is to build a model to show the relationship between input variables and the possibility of the binary outcome. The logistic function is the basement of it, and the logistic function helps to explain the outcome as the possibility of being a particular class. By using a technique called maximum likelihood estimation [2], Logistic Regression estimates the coefficient of the logistic function[3], when researchers need to classify a group of patients, they can represent a common trait of one-half of the group, and 0 represents another half. The logistic function is also called the Sigmoid function; its simple formula is shown below:

$$g(z) = \frac{1}{1 + e^{-z}} \tag{1}$$

$\theta\hat{} = \text{argmax}_{\theta \in \Theta} Ln(\theta; y)$.

This process includes some iterative optimization ways like Newton's method [4]. In Logistic Regression, it supposes that the relationship between the predictors and the log odd of the result variables is linear. However, it can be non-linear when interaction terms or polynomial features are applied. Logistic Regression can solve both categorical and continuous input variables. The disadvantage is that the assumption of the linear relationship between predictors and the outcome is not always true. To solve this problem, researchers often select high-quality data. It is also sensitive to outliers.

5. Random Forest

Random Forest is a famous method of machine learning that is used in spatial-spectral classification in remote sensing. It is an ensemble classifier that makes classification more accurate by combining multiple decision trees [5]. In this way, every tree can be treated in a random subset of the training data input features. Here Gini index is used to classify a group of trees [6]. The Gini index formula is shown below:

$$\text{Gini} - \text{index}(D, A) = \sum_{v=1}^{V} \frac{D_v}{D} \text{Gini}(D^v) \tag{2}$$

The working way of the method is to first build many decision trees using different subsets of the training data and features. Then, each tree votes on the class distributions for each pixel on their own individual decision rules. The final class label for a given pixel is gained based on the most votes of all the trees. Handling non-linear and complex relationships between spectral bands and land cover classes is one of the advantages of the Random Forest because it can help classify a huge group of data into specific small groups. Moreover, it is less likely to be too similar to other machine learning

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algorithms because it uses random subsets of the training data and features. In general, Random Forest is a powerful and widely used method for spectral classification in remote sensing because of its high ability to solve complex relationships between spectral bands and land cover classes.

6. Experiment

These 3-stage method for hyper spectral image classification. The first stage is a pre-processing step where the most correlated nested window is found, and the data is reconstructed based on the Pearson correlation for each pixel. Then, PCA is used to reduce the dimension of the reconstructed data. The second stage is a semi-supervised classification step where an SVM-type method, SVC, is trained, and an estimated probability tensor consisting of the probability maps for all classes is produced. The last stage is a post-processing step where a smoothed total variation model is applied to remove isolated misclassified pixels. The method's superiority is that it fully explores spatial and spectral information of hyper spectral images so that we only need a very small number of labeled pixels to obtain higher accuracy than other methods. The pre-processing step enhances the consistency of spectral signatures of adjacent pixels, especially for those pixels that are located in a large homogeneous area and have varying inner-class spectra. The post-processing step further improves the classification result by ensuring connectivity across spatial homogeneous regions using the spatial positions of the pixels. The smoothed total variation model used here can simultaneously enhance spatial homogeneity by denoising while segmenting the image into different classes.

An idea and computationally feasible method is called the semi-supervised method. They require a small amount of labeled data for training. For example, the support vector machine performs well in hyperspectral images, the pixel classification method can be enhanced by analyzing the space dependence of nearby pixels, Smoothed total variation model has been employed for denoising and segmentation. The square fixed-size space of pixels is used to extract features in hyperspectral images. (joint sparsity representation.jsr) means that constructing JSR on local square patches makes full use of spatial information. Some pixels in the edges or corners do not have similar specifications to the center pixel. When spatial homogeneity and heterogeneity exist simultaneously, the fixed-size window will fail. Therefore, the nested sliding window is designed to look for an optimum nesting square window with the maximum Pearson correlation average value between the window center and other pixels. Then, the spectrum of the center pixel is replaced by the product of the weighted Pearson correlation vector in the optimal windowing window and the spectra of the pixel. The shape adaptive region (SA) of the pixel is learned by constructing a locally smooth irregular polygon in the first principal component. Polynomial forward filtering (LAP) and intersecting confidence interval rules (ICI) are adopted, and then shape adaptive jsr is applied to properly explore the spatial and spectral information in the SA region. Instead of using jsr, the spectrum of each pixel is reconstructed with its SA region.

More and more methods based on spectral space have been used to solve hyperspectral image classification. A combination of spectral gradient, SVM, and spatial random forest becomes a new method to solve the HSI classification. Firstly, the spectral gradient technique can solve the original hyperspectral data [7], and more detailed information can be obtained. Second, the data from the first step is put into the SVM to get a probability output. Simultaneously, the SVM still helps to obtain spatial context information. Here, the new spectral vectors can be considered to get into the SVM model with a sigmoid function to get probability output by fitting the classification results. Then, using a S=D*D square spatial surrounding the test vector to get SVM outputs different-scaled neighboring pixels SVM outputs. Then, mix the multiscale spatial features with corresponding weights and use it as an input into the random forest classifier[8]. The experiment includes three HSI datasets: AVIRIS Indian Pines, Salinas, and ROSIS Pavia University. In general, the new methods get a more accurate classification and Kappa coefficient [9]. The use of spectral gradient gets more detailed information, and the sigmoid function corresponds to the classification results and develops the nonlinear structure. That result proves that this method has a great advantage in the classification accuracy and the Kappa coefficient. The method is generally good at obtaining detailed information through spectral gradient.

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In addition, it develops the performance of classification by the nonlinear structure created by the Sigmoid function.

7. Datasets

In this paper, some datasets are introduced: Salinas A, Salinas, Indian Pines, and Pavia U. A Salinas A dataset is a commonly used hyperspectral dataset that was collected over the Salinas Valley in California by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor. It has 224 spectral bands and 512x217 pixels. For classification and analysis tasks in remote sensing, this dataset is frequently utilized. Another hyperspectral dataset was gathered by the AVIRIS sensor over the Salinas Valley and is called the Salinas dataset. It features 224 spectral bands and 512x217 pixels, just like Salinas A. The primary distinction is adding additional ground truth data, including named objects and areas of interest. This dataset is frequently used by researchers for feature extraction and land-use classification research. The Indian Pines dataset is a hyperspectral collection made over an agricultural area in Indiana, USA, with the AVIRIS sensor. 145x145 pixels and 224 spectral bands make up the image. For hyperspectral image research in relation to agricultural applications, crop analysis, and land categorization, this dataset is very intriguing. Another hyperspectral dataset was obtained over the Pavia University campus in Italy by the Reflective Optics System Imaging Spectrometer (ROSIS) sensor. It features 103 spectral bands and a spatial resolution of 610x340 pixels. The tasks of land classification, feature extraction, and anomaly detection frequently employ this dataset.

8. Conclusion

In conclusion, this study throws light on remote sensing data classification and its practical value. The possible advantages and limitations of pixel-level processing approaches are investigated, such as brightness control and noise reduction. Furthermore, research into classification algorithms such as Support Vector Machines, Logistic Regression, and Random Forest has yielded critical insights into their accuracy and application in remote sensing analyses. Experimenting with different datasets has reaffirmed the usefulness of the suggested approaches, demonstrating their capacity to improve classification accuracy with limited labeled data. The field of remote sensing data analysis will be improved by recognizing these realities and exploiting the approaches given, unlocking their potential for resource mapping, environmental monitoring, and other critical applications.

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