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Techniques used for Remote Sensing Image Classification: A Review

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ABSTRACT:
In this paper, the pixel-wise and object-based picture classification algorithms were both explored. Artificial Neural Networks (ANNs), Classification Trees (CTs), and Support Vector Machines (SVMs) are among the advanced classification methods investigated in this study (SVMs). The advantages and disadvantages of various categorization systems are also highlighted.

Keywords: Remote Sensing, Image Classification,

Introduction

Many socioeconomic and environmental applications, such as urban and regional planning, natural resource conservation and management, and so on, rely on regularly updated land use and land cover data [Homer et al., 2007; Lu and Weng, 2007; Jensen, 2009]. Remote sensing data covering a large geographic area with high temporal frequency gives a unique chance to gather land use and land cover information through the process of image interpretation and categorization. Remote sensing image classification techniques have been used to provide current land use and land cover data at various scales since the 1980s. In the 1980s and 1990s, most classification methods employed the image pixel as the fundamental unit of analysis, with each pixel labelled as a different land use land cover class. The pixel is the basic analytic unit in a number of classification methods. Unsupervised (k-means and ISODATA) and supervised (maximum likelihood, artificial neural network, decision tree, support vector machine, random forests) classification methods have all been developed [Zhang et al., 2005; Alajlan et al., 2012].

The purpose of this research is to help analysts, especially those new to remote sensing, choose the best classification approach for accurately classifying remotely sensed satellite pictures. This article discusses recent developments in classification approaches such as Artificial Neural Networks (ANN), Classification Trees (CTs), and Support Vector Machines (SVMs). On the other hand, the most common problems associated with them have been mentioned.

Image Classification Methods

Pixel wise image classification

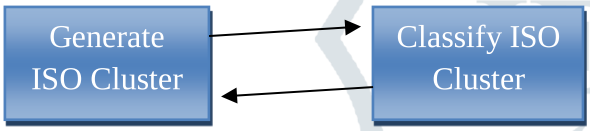
Pixel-wise classification methods, which are the most widely used remote sensing image classification approach, assume that each pixel is pure and are generally labelled as a single land use land cover category [Fisher, 1997; Xu et al., 2005]. This approach treats remote sensing data as a collection of spectral pixels, with spectral characteristics and transformations (e.g. major components, vegetation indices, and so on) input into per-pixel classifiers. Pixel-wise classification methods may be divided into two types:

Unsupervised Classification

An unsupervised classifier splits a remote sensing image into a number of classes based on the natural groupings of the image values without the use of training data or prior knowledge of the study location [Lillesand et al., 2004; Puletti et al., 2014].

Unsupervised categorization consists of two essential steps:

- Clusters should be generated
- Classify



We start by creating "clusters" with remote sensing software. The following are some of the most prevalent picture clustering algorithms:

- K-means and its variation (most widely used unsupervised classification methods)
- ISODATA (Iterative Self-Organizing Data Analysis)

After you've decided on a clustering strategy, you'll need to figure out how many groups you want to make. You may construct 8, 20, or 42 clusters, for example. There are more pixels that are similar inside groups with fewer clusters. The variability within groupings increases as the number of clusters climbs.

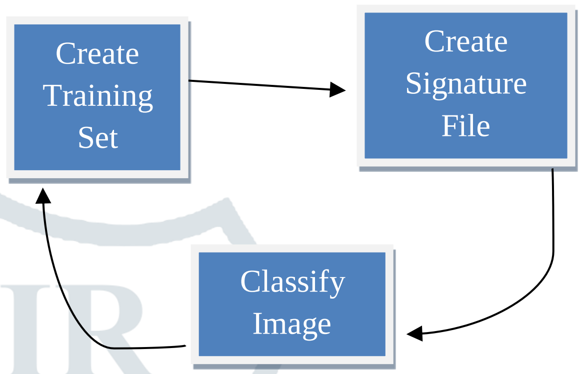
These clusters are unclassified, to be clear. The final stage is to assign particular land cover classifications to each cluster. You can pick the clusters that best show vegetation and non-vegetation, for example, if you want to distinguish vegetation and non-vegetation.

The Self-Organizing Maps (SOM) technique and hierarchical clustering algorithms have recently been developed for unsupervised classification [Goncalves et al., 2008].

Supervised Classification

An image analyst uses supervised classifiers to select representative sample sites with known class types (i.e. training samples), compare the spectral properties of each pixel in the image to those of the training samples, and then label the pixel to the class type using decision rules [Lillesand et al., 2004]. The three basic steps of supervised classification are as follows:

- Areas of training to be chosen
- Create a signature file.
- Classify



For supervised picture classification, you must first generate training examples. You can identify urban regions, for example, by highlighting them in the image. Then you'd keep filling in the blanks with training locations until the image was complete.

IKONOS is a supervised categorization system.You continue to construct training samples for each land cover class until each class has representative examples. As a consequence, a signature file including the spectral information of all training samples would be formed.

The final step would be to use the signature file to conduct a categorization. The next step is to select a categorisation algorithm, such as:

- Maximum likelihood
- Minimum-distance
- Principal components
- Support vector machine (SVM)
- Iso cluster

Modern Classification Techniques

Although the quality and spatial resolution of remotely sensed data is rising, this does not guarantee more precise feature extraction. The image classification methods used are an important factor in increasing accuracy (Robert et al., 2010). Advanced image classification methods such as ANN, SVMs, and CTs are extensively utilised and have consistently outperformed classical classifiers. They're especially well-suited for combining non-spectral data into categorisation. A brief overview of each categorization is provided below. Readers who desire a more detailed discussion of a particular classifier can consult the references provided below.

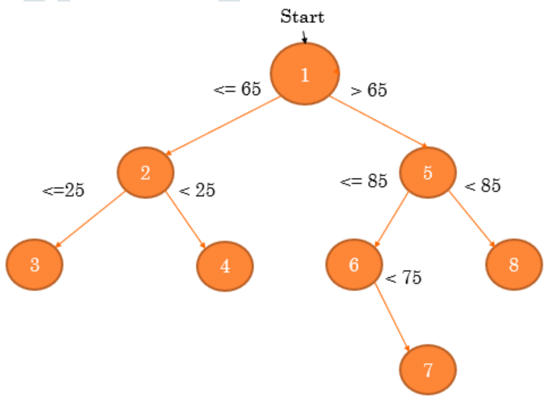
Artificial Neural Networks (ANN)

In order to give meaningful labels to image pixels, ANN is a sort of artificial intelligence that replicates some of the functions of the human brain. Because ANN-based classification uses a nonparametric method, adding more data to the classification process to improve classification accuracy is straightforward (Abburu and Golla, 2015). An ANN is built up of layers, each of which has a group of processing units called neurons. All neurons on a certain layer are connected to all neurons on preceding and subsequent layers via weighted connections. During the training phase, the ANN learns about the regularities in the training data and then creates rules that may be applied to the unknown data (Foody, 1999). Some of the ANN algorithms that may be used to categorise remotely sensed images are MLP, SOM, and Fuzzy ArtMap. The Fuzzy ArtMap approach has shown to be the most efficient, followed by the MLP. SOM has the lowest categorisation accuracy in the majority of articles. All of these algorithms rely largely on the operators' understanding of how to set up their parameters for optimal outcomes. MLP involves a complete retraining of the network. Even for small test areas, this may mean a long training time. Fuzzy ArtMap, on the other hand, can solve large-scale problems in just a few training epochs.

The only drawback with Fuzzy ArtMap is that it is subject to noise and outliers, which can lower classification accuracy. Unlike MLP and Fuzzy ArtMap, SOM can differentiate multimodal classes. SOM, on the other hand, frequently results in a substantial proportion of pixels that are unlabeled.

Classification trees (CTs)

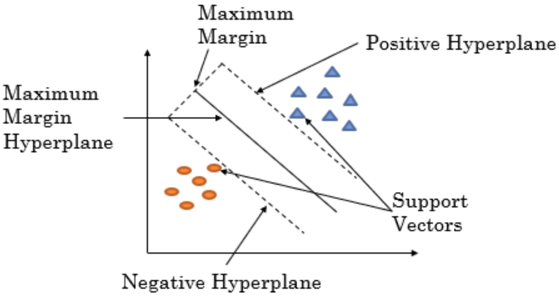
The notion of classification trees (CTs) was developed by Breiman et al (1984). CT is a nonparametric, iterative, and progressive pattern recognition approach based on hierarchical principles. A CT is made up of the root node (the starting node), non-terminal nodes (those connecting the root node to all other internodes), and the terminal node. It predicts class membership by recursively partitioning a dataset into homogeneous subsets using a variety of binary splitting methods (Tso and Mather, 2009). These criteria are based on 'impurity' and are established using statistical approaches using training data. ' If every pixel in a node belongs to the same category, the node is pure, and the impurity is zero. If the logical condition at a specific node is satisfied, the left branch is chosen; otherwise, the right branch is chosen. The procedure is continued until the node has become pure and has been designated as a terminating node.



Classification Tree

Support Vector Machines (SVMs)

The Support Vector Machine, is a popular Supervised Learning tool for both classification and regression problems. However, it is largely used in Machine Learning to solve problems with classification. The goal of the SVM method is to discover the best line or decision boundary for categorising n-dimensional space into classes so that subsequent data points may be easily placed in the right category. The best choice boundary is referred to as a hyperplane. SVM is used to choose the extreme points/vectors that help build the hyperplane. The approach is known as a Support Vector Machine, and support vectors are the extreme examples. Consider the picture below, which shows how a decision boundary or hyperplane is used to classify two separate categories:



Pros and Cons Of modern Classification Techniques

ANN Pros

- uses non-parametric classifiers
- has a high computation rate of large datasets
- efficiently handles noisy inputs.

ANN Cons

- it's tough to comprehend how the outcome was obtained
- training process is slow.
- An issue of overfitting may arise.
- based on criteria set by the user

CTs Pros

- uses non-parametric classifiers
- it does not require an extensive design and training
- easy to integrate multi source data
- accurate computational efficiency is good.

CTs Cons

- calculation becomes complex when various outcomes are co related.

SVMs Pros

- uses non-parametric classifiers
- provides a good generalization
- controlled overfitting
- Computational efficiency is high
- work effectively with small training sets and data with a lot of dimensions
- Other classifiers are frequently outperformed.

SVMs Cons

- Its structure is difficult to comprehend.
- Depending on criteria set by the user
- Finding the best settings is difficult.
- Training takes a lot of time.

Conclusion

For socio-economic planning and environmental applications, remote sensing image classification algorithms may be used to extract information on land use and land cover. The object-based classification strategy outperformed both unsupervised and supervised pixel-based classification algorithms.

This paper gives a brief summary of numerous classification systems, highlighting their advantages and disadvantages. It strongly emphasises contemporary classification methods such as ANN, SVMs, and CTs. SVM is one of the best classification algorithms for remote sensing, but each option has its own set of advantages that you may weigh.

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