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Comparison of support vector machine, neural network, and CART algorithms for the land-cover classification using limited training data points

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ABSTRACT

Support vector machine (SVM) was applied for land-cover characterization using MODIS time-series data. Classification performance was examined with respect to training sample size, sample variability, and landscape homogeneity (purity). The results were compared to two conventional nonparametric image classification algorithms: multilayer perceptron neural networks (NN) and classification and regression trees (CART). For 2001 MODIS time-series data, SVM generated overall accuracies ranging from 77% to 80% for training sample sizes from 20 to 800 pixels per class, compared to 67–76% and 62–73% for NN and CART, respectively. These results indicated that SVM's had superior generalization capability, particularly with respect to small training sample sizes. There was also less variability of SVM performance when classification trials were repeated using different training sets. Additionally, classification accuracies were directly related to sample homogeneity/heterogeneity. The overall accuracies for the SVM algorithm were 91% (Kappa = 0.77) and 64% (Kappa = 0.34) for homogeneous and heterogeneous pixels, respectively. The inclusion of heterogeneous pixels in the training sample did not increase overall accuracies. Also, the SVM performance was examined for the classification of multiple year MODIS time-series data at annual intervals. Finally, using only the SVM output values, a method was developed to directly classify pixel purity. Approximately 65% of pixels within the Albemarle–Pamlico Basin study area were labeled as "functionally homogeneous" with an overall classification accuracy of 91% (Kappa = 0.79). The results indicated a high potential for regional scale operational land-cover characterization applications.

1. Introduction

MODIS (Moderate Resolution Imaging Spectroradiometer) data has been increasingly used to characterize land-cover and monitor vegetation phenology at regional and global scales, since being launched in 2000. One of the most appealing aspects of MODIS data is its unique combination of spectral, spatial, radiometric, and temporal resolutions; which are considered to be substantially improved over other similar observation systems (Townshend and Justice, 2002). It has become common practice to utilize MODIS time-series data to monitor vegetation characteristics and condition using phenology information and derived metrics that can provide additional information to differentiate spectrally confusing cover types (Defries and Townshend, 1994; Friedl et al., 2002; Loveland et al., 2000). At global scales, Friedl et al. (2002) developed an operational annual land-cover mapping approach using MODIS time-series data. For regional applications, a large number of researchers have been exploring MODIS-based classification protocols (Knight et al., 2006), algorithms (Hansen et al., 2003; Lobell and Asner, 2004), and validation approaches (Giri et al., 2005).

The use of MODIS time-series data, however, can substantially increase data input volume (features/dimensions) for classification applications. For example, many researchers have applied a large number of MODIS spectral and temporal band combinations in their classifications (Carrão et al., 2008; Friedl et al., 2002; Knight et al., 2006; Xavier et al., 2006; Xiao et al., 2005; Wardlow et al., 2007). In addition to the increasing computational requirements, the Hughes phenomenon can also impact classification performance (Bishop, 2006; Camps-Valls et al., 2008; Gualtieri and Cromp, 1999; Melgani and Bruzzone, 2004). Also, the availability of training pixels is often limited in practice, which may reduce the generalization of the classifier. Feature selection can be used to reduce the impact of Hughes phenomenon, but aggressive feature reduction may lead to information loss (Melgani and Bruzzone, 2004). These problems have been widely addressed in hyperspectral remote sensing applications that also use hundreds

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of input features for image classification and object detection. Recent studies have suggested that support vector machine (SVM) can provide good results for hyperspectral remote sensing classification and superior results have been reported compared to traditional remote sensing classification algorithms such as maximum likelihood (ML), k-nearest neighbor, and neural networks (NN) (Huang et al., 2002; Melgani and Bruzzone, 2004; Pal and Mather, 2005). The most appealing property of SVM was the high capacity for generalization with relatively small numbers of training data points (Bishop, 2006; Pal and Mather, 2005). However, the potential of SVM has not received much attention for MODIS time-series data classification. Specifically, the performance of SVM classification has not been thoroughly assessed with regard to training sample sizes, and training data variations and characteristics (i.e., homogeneous vs. heterogeneous).

The objective of this study was to implement and assess SVM classification performance using MODIS time-series data. We compared SVM approach with the two most commonly used nonparametric classification algorithms: (i) multilayer perceptron neural networks (NN); and (ii) classification and regression trees (CART). The experiment was designed for examining the classification performance using relatively small training samples. We focused on the impact of training sample sizes ranging from 20 to 800 pixels per class using randomly selected samples from a large pool of training data points. Accuracy assessments were performed using multiple independent reference datasets. In addition to the accuracy assessment for pure pixels, we also assessed mixed pixels, because many MODIS pixels (250 m GSD) were generally a mixture of two or more cover types. The research goal was to provide insights for regional scale land-cover classification applications using MODIS time-series data.

2. Background

2.1. SVM classifier

Early development of SVM started in 1970s and the popularity of SVM for pattern recognition and classification is actually surged in the late 1990s (Vapnik, 1995; Vapnik, 1998). In remote sensing, SVM was primarily used for the hyperspectral image classification and object detection (Gualtieri and Cromp, 1999; Melgani and Bruzzone, 2004); although researchers have recently expanding its application for multispectral remote sensing data (Foody and Mathur, 2004; Huang et al., 2002; Pal and Mather, 2005). Melgani and Bruzzone (2004) and Huang et al. (2002) provided a detailed introduction of SVM to the remote sensing community. Mountrakis et al. (2011) summarized empirical results from over 100 articles using the SVM image classification algorithm. The primary advantage of SVM was good generalization capability with limited training samples. The authors acknowledged SVM's limitations in parameter selection and computational requirements. However, SVM provided superior performance compared to most other image classification algorithms for both real-world remote sensing data and simulated experiments.

Using hyperspectral remote sensing data, Melgani and Bruzzone (2004) performed a detailed comparison of SVM, conventional K-nearest neighbor, and a radial basis neural network. Their results indicated that SVM substantially outperformed the other two classifiers. They concluded that SVM was less sensitivity to the Hughes phenomenon, thus feature selection procedure may not be needed for high dimensional dataset. Furthermore, they compared a range of SVM multi-class classification strategies including one-against-all, one-against-one, and hierarchical tree-based classification scheme or approaches. The results from these approaches appeared to be quite similar. The superior performance from SVM was also reported by (Camps-Valls et al., 2004; Camps-Valls and Bruzzone, 2005; Gualtieri and Cromp, 1999), particularly with respect to the classification of hyperspectral remote sensing data.

Huang et al. (2002) implemented SVM classification for a spatially degraded Landsat Thematic Mapper (TM) data. The SVM classification accuracy was superior to that obtained using a maximum likelihood algorithm and a decision tree algorithm. However, there was no advantage to use SVM compared to a neural network classifier. It should be noted that the input feature dimension in their study was rather small. In addition, the sizes of training samples were fairly large (i.e., 2–20% of entire image). The advantage of SVM thus may not be evident in those scenarios. Camps-Valls et al. (2008) presented a novel family of kernel-based methods for time-series image classification. The SVM approach demonstrated superior performance compared to neural networks for high dimension time-series spectral data from multiple sensors. Similarly, Bovolo et al. (2010) approached image change detection as an outlier detection problem. SVM provided a robust outlier detection capability in their study. Carrão et al. (2008) employed SVM to examine the impacts of MODIS temporal and spectral factors for a general land-cover classification in Portugal. Their findings indicated that a limited number ($n = 3$) of MODIS composited images, if selected appropriately, provided sufficient image classification accuracy. The results were consistent with those presented by Shao and Lunetta (2011).

In addition to the SVM-based categorical classification, there is also growing interests in the SVM regression for estimating subpixel land cover proportions (Brown et al., 2000). In general, the SVM represents a novel approach compared to conventional ML, CART, and NN classifiers. Currently, only a few studies have applied SVM algorithm for time-series MODIS image classification (Carrão et al., 2008). Additional SVM applications for regional scale land-cover classification need to be conducted to better understand performance. The implementation of SVM for MODIS time-series data is of particular interest for operational regional-scale land cover characterization.

2.2. NN and CART classifications

Neural network classification algorithms have long been used for remote sensing image classification (Paola and Schowengerdt, 1995; Richards and Jia, 1999). Many have suggested that these types of models are superior to traditional statistical classification approaches (i.e., maximum-likelihood classification), because they do not make assumptions about the nature of data distribution, and the function is simply learned from training samples. Several neural network models are commonly applied (Tasdemir and Merenyi, 2009). ARTMAP models have been increasingly used due to their stability and computational performance (Carpenter et al., 1997). For instance, Gopal et al. (1999) used fuzzy ARTMAP to classify annual sequence of composited NDVI data. They found an increase of 7.0% in overall accuracy compared to a maximum likelihood classification. The same ARTMAP algorithm was also used by other researchers for time-series NDVI image classification at regional and global scales. The results from ARTMAP algorithm were consistently superior to those obtained from a maximum likelihood classification. Bagan et al. (2005) employed the self-organizing map (SOM) neural network technique to classify land-cover types using 16-day composites of MODIS Enhanced Vegetation Index (EVI) data. Superior classification results were found compared with those obtained using maximum likelihood classification method. Using time-series MODIS NDVI data, Shao et al. (2010) characterized specific crop types with a multi-layer perceptron (MLP) neural network model. The principal challenges associated with MLP implementation was the adjustment of network parameters (network architecture, learning rate, and momentum).