MACHINE LEARNING IN REMOTE SENSING DATA PROCESSING

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ABSTRACT

Remote sensing data processing deals with real-life applications with great societal values. For instance urban monitoring, fire detection or flood prediction from remotely sensed multispectral or radar images have a great impact on economical and environmental issues. To treat efficiently the acquired data and provide accurate products, remote sensing has evolved into a multidisciplinary field, where machine learning and signal processing algorithms play an important role nowadays. This paper serves as a survey of methods and applications, and reviews the latest methodological advances in machine learning for remote sensing data analysis.

1. INTRODUCTION

Remote sensing is the field of science studying and modeling the processes occurring on the Earth's surface and their interaction with the atmosphere [1]. Earth observation at local and global scales is nowadays an increasing need. By monitoring urban growth, estimating temperature or ocean salinity, and identifying objects on the surface, remote sensing provides valuable information for policy and decision makers, as well as for tourism or defense applications. These objectives are possible because materials in a scene reflect, absorb, and emit electromagnetic radiation in a different way depending of their molecular composition and shape. Remote sensing exploits this physical fact and deals with the acquisition of information about a scene (or specific object) at a short, medium or long distance.

According to the type of energy resources involved in the data acquisition, remote sensing imaging instruments can be *passive* or *active*. In this paper we will focus on passive sensors which have experienced a great evolution in the last decades, and pose challenging problems for the machine learning and signal processing communities. Passive systems exploit solar radiation to capture the emergent radiation, which is acquired by an airborne or satellite spectrometer at different wavelengths. The acquired signal or spectral signature is

This work was partially supported by projects from the Spanish Ministry of Science TEC2006-13845/TCM, CSD2007-00018 and AYA2008-05965-C04-03.

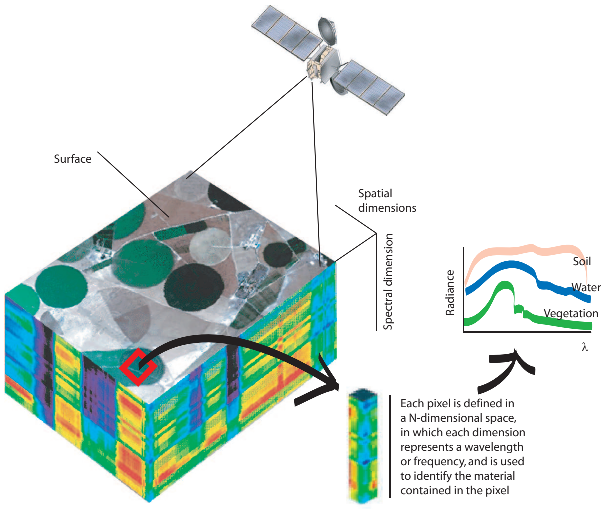

Fig. 1. Principle of imaging spectroscopy.

known as *spectrum* and is used to identify materials in the scene. Figure 1 shows the principle of imaging spectroscopy to perform satellite remote sensing. The resulting multispectral image consists of a simultaneous acquisition of spatially coregistered images, in several, spectrally contiguous bands from a remotely operated platform [1, 2].

The diversity of objectives and the special characteristics of the data give rise to the use of a wide range of machine learning and signal processing algorithms. The statistical characterization of remote sensing images turns to be difficult because of pixel's high dimensionality, presence of different kinds of noise sources and uncertainty, their inherent non-linear nature, and the high spatial and spectral redundancy. Machine learning has been successfully applied in remote sensing for classification, regression, clustering, coding, or source separation. However, we feel that promising new learning paradigms, such as transfer, active, structured, reinforcement, semisupervised or manifold learning, have been payed little or no attention. This paper reviews both traditional and new trends in machine learning for remote sensing data processing with the main goal of estimulating research and development in both directions.

2. TRADITIONAL MACHINE LEARNING FOR REMOTE SENSING

In this section, we review the traditional machine learning approaches to remote sensing applications. Only the most relevant applications are revised: classification, feature selection and extraction, regression and unmixing.

2.1. Image classification

Classification maps are the main product of remote sensing image processing. In the last years, data-driven approaches have gained relevance in the remote sensing community. In particular, non-parametric methods have demonstrated good performance. Supervised and unsupervised are revised here.

2.1.1. Supervised Image Classification

These methods use labeled information about class membership of single pixels (labeled by expert users) to build a model able to generalize to the whole image (or set of images). At present, the most successful methods are neural networks [3, 4] and support vector machines [5]. The latter have been applied to both multispectral [6,7] and hyperspectral [5,8,9] data in a wide range of domains, including object recognition [10], landcover and multi-temporal classification [9,11,12], and urban monitoring [13] to name a few. Another field of growing interest is that of classifier ensembles [14, 15] and boosting methods [16].

2.1.2. Unsupervised Image Classification

Unsupervised classification of remote sensing images is a critical problem in many applications, either for visualization and monitoring of similar areas in the scene or as a pre-processing step for supervised classifiers. Many clustering methods have been designed, such as rule-based [17], neural networks [18–20], or based on SVMs [21]. Three approaches dominate the field. First, fuzzy clustering has been used alone [22, 23] or combined with multiobjective optimization [24] for exploiting spatially membership relations. Second, fusion of multisource information has been conducted either with graph-cuts [25], projection pursuit [26], hierarchical clustering [27], or Markov random fields [28] for contextual regularization. Also, multicomponent image segmentation with self-organizing maps (SOM) and hybrid genetic algorithms [20] have been proposed. Finally, it is worth mentioning the use of dynamic clustering strategies for spatio-temporal reasoning [29] and visualization [30].

2.1.3. Multitemporal Classification and Change Detection

Multitemporal and change detection problems are very active because of the increasing availability of complete time series of images and the interest in monitoring Earth's changes at local and global scales. On the one hand, many multi-temporal supervised methods have been used during the last years, such as evidence reasoning [31], generalized least squares [32], neural networks [33] or support vector machines (SVMs) [34, 35]. Hidden Markov random fields [36] and fuzzy-based approaches [37] have been also used to link time-varying statistics. On the other hand, change detection approaches typically use image subtraction or ratioing, change vector analysis, or cross-correlation analysis [1]. Recently, neural networks [38] and kernel methods [9] have been used. Composite kernels have been specifically designed for the combination of multitemporal, multisensor and multisource information [9, 39]. Recent advances focus on the reduction of the user intervention, either by using semi- or unsupervised methods [40, 41].

2.2. Feature Selection and Extraction

A critical issue when working with high dimensional datasets, such as hyperspectral images, is that the computational time is increased and the high collinearity and presence of noisy bands can degrade the quality of the model. But maybe more important is the study of the relative relevance of the acquired bands to perform a given task. Remember that spectral bands have a physical meaning and can be related to the properties of the elements to be identified or modeled.

Feature selection has been studied in remote sensing under classical discriminative criteria [42]. Lately, advanced machine learning methods have been used, such as genetic algorithms [43], or SVM-based recursive feature elimination [44]. Recently more attention has been focused on feature extraction methods. Even though the use of linear methods such as PCA or PLS is quite common, recent advances to cope with nonlinearities in the data based on multivariate kernel machines have been presented [45].

2.3. Signal Unmixing

Pixels are invariably a mixture of the signatures of the various materials found within the spatial extent of the ground instantaneous field view. An important problem in remote sensing is the development of automatic extraction methods of the spectral pure pixels (known as *endmembers*) directly from the image. These pure pixels are the basis to express all pixels as a linear (or non-linear) combination of them, and this, in turn, allows subpixel detection [2] or mineral mapping [46]. Some classical techniques for this purpose include the N-FINDR algorithm [47], the vertex component algorithm (VCA) in [48], and an orthogonal subspace projection (OSP) technique in [49], among others [50]. Selection of the free parameters and inclusion of spatial information in the unmixing process are key issues nowadays [51]. Recently support vector domain description (SVDD) has been also used to select the pure pixels [45].

2.4. Regression and Model Inversion

Robust, fast and accurate regression tools are a critical demand in remote sensing. The estimation of biophysical parameters is of special relevance in order to better understand the environment dynamics at local and global scales [1]. The inversion of analytical models introduces a higher level of complexity, induces an important computational burden, and sensitivity to noise becomes an important issue. In the recent years, nevertheless, the use of *empirical models* adjusted to learn the relationship between the acquired spectra and actual ground measurements has become very attractive. *Parametric* models have some important drawbacks, which typically lead to poor prediction results on unseen (test) data. As a consequence, *non-parametric* and potentially *non-linear* regression techniques have been effectively introduced, such as neural networks [52, 53], support vector regression (SVR) [54, 55], relevance vector machines (RVM) [56], or Gaussian Processes (GP) [57]. Even been more accurate than analytical models, they lack interpretability and rely on training data from the observed scene, which limits its extensive use.

3. NEW TRENDS IN MACHINE LEARNING FOR REMOTE SENSING

The special characteristics of the acquired data motivates the continuous research in machine learning methods for tackling particular remote sensing problems. In this section, we summarize some promising machine learning paradigms of recent application in remote sensing.

3.1. Manifold Learning

Recently the field of *manifold learning* has appeared as a powerful framework to analyze nonlinearities in the data. The field is related to that of *dimensionality reduction* and *nonlinear feature extraction*, which is scattered throughout computer science, machine learning, image processing and cybernetics. The main goal in manifold learning is to map high dimensional data into a lower dimension while preserving the main features of the original data for better analysis. In this way, visualization and understanding of high-dimensional data becomes feasible. Traditional linear dimensionality reduction methods fail in describing the inherent structure of remote sensing data. Consequently some preliminary works using nonlinear transforms have been presented, such as Isomap [58, 59], Laplacian methods [60, 61] or Local Linear Embedding [59, 62]. Besides, some algorithms that analyze the *intrinsic dimensionality* of hyperspectral images can be mentioned [63].

3.2. Semi-supervised Learning

A related field to manifold learning is semi-supervised learning, which is concerned in developing models that exploit the (typically few) labeled data and the wealth of unlabeled samples to model the manifold data structure. In remote sensing, several methods have been developed, either *generative* or *discriminative*. The estimation of the conditional density to be included in generative models have been extensively exploited [64]. Recently, many graph-based methods have been developed for classification [61, 65], regression [55], and target detection [66, 67]. Also, the design of cluster and bagged kernels have been successfully presented [68]. Also the transductive SVM has been applied for image classification [69, 70] and change detection [40]. In [71], a semisupervised kernel Fisher discriminant classifier was proposed. These methods, however, cannot readily applicable to large scale problems with millions of unlabeled samples, as is often the case.

3.3. Transfer Learning

A common problem in remote sensing is that of updating land-cover maps by classifying temporal series of images when only training samples collected at one time are available. This is known as transfer learning or domain adaptation. The problem was initially tackled with partially unsupervised classifiers, under parametric formalisms [72] and neural networks [73]. The approach was then successfully extended to domain adaptation SVM (DASVM) [74]. A related problem is also that of classifying an image with samples from different images, which induces the sample selection bias or covariance shift problems. These problems have been recently presented by defining proper kernel machines [75].

3.4. Active Learning

In remote sensing, application of active learning methods that select the most relevant samples for training is quite recent. A SVM method for object-oriented classification was proposed in [76], while maximum likelihood classifiers for pixel-based classification was presented in [77]. Recently, this approach was extended in [78] by proposing boosting to iteratively weight the selected pixels. In [79, 80] information-based active learning was proposed for target detection, and in [81], a model-independent active learning method was proposed for very-high resolution satellite images.

3.5. Structured Learning

Most of the techniques revised so far assume a simple set of outputs $\mathcal{Y}$, for instance binary labels $\mathcal{Y} = \{-1, 1\}$. However, more complex output spaces can be imagined, e.g. predicting multiple labels (land use and land cover simultaneously), multi-temporal image sequences, or abundance fractions. Such complex output spaces are the topic of structured learning, one of the most recent developments in machine learning. Only a computer vision application [82] and the preliminary results in [83] have been presented for image processing.

4. CONCLUSIONS

The field that machine learning occupies in remote sensing has been summarized in this paper. Attention has been paid not only to the standard machine learning paradigms (classification, regression and feature extraction/selection), but also to recently and promising ones, such as manifold, semisupervised, active, transfer and structured learning. The special peculiarities of the images open the field for research and development of new methods. And viceversa, the new learning paradigms available offer new ways of looking at old, yet unsolved, problems.

5. ACKNOWLEDGMENTS

The author would like to thank Mr. Devis Tuia from the University of Lausanne (Switzerland) for his valuable pieces of advice and useful discussion and comments about this work.

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