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Converting local spectral and spatial information from a priori classifiers into contextual knowledge for impervious surface classification

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ABSTRACT

A classification model was demonstrated that explored spectral and spatial contextual information from previously classified neighbors to improve classification of remaining unclassified pixels. The classification was composed by two major steps, the a priori and the a posteriori classifications. The a priori algorithm classified the less difficult image portion. The a posteriori classifier operated on the more challenging image parts and strived to enhance accuracy by converting classified information from the a priori process into specific knowledge. The novelty of this work relies on the substitution of image-wide information with local spectral representations and spatial correlations, in essence classifying each pixel using exclusively neighboring behavior. Furthermore, the a posteriori classifier is a simple and intuitive algorithm, adjusted to perform in a localized setting for the task requirements. A 2001 and a 2006 Landsat scene from Central New York were used to assess the performance on an impervious classification task. The proposed method was compared with a back propagation neural network. Kappa statistic values in the corresponding applicable datasets increased from 18.67 to 24.05 for the 2006 scene, and from 22.92 to 35.76 for the 2001 scene classification, mostly correcting misclassifications between impervious and soil pixels. This finding suggests that simple classifiers have the ability to surpass complex classifiers through incorporation of partial results and an elegant multi-process framework.

1. Introduction

Impervious surface detection is an important topic in remote sensing applications. A variety of research has been conducted on classification methods for imperviousness estimation based on remotely sensed images (Weng, 2007). Examples of these methods include multivariate regression (Bauer et al., 2005; Yang, 2006), spectral mixture (Wu and Murray, 2003; Lu and Weng, 2006; Powell et al., 2007; Franke et al., 2009) and machine learning models (Herold, 2003; Yang et al., 2003; Dougherty et al., 2004; Lee and Lathrop, 2006; Mohapatra and Wu, 2008; Esch et al., 2009; Hu and Weng, 2009; Mountrakis et al., 2011).

However, the majority of the imperviousness classification methods are pixel-based and do not consider spatial and contextual information from neighboring pixels that may improve classification accuracy. Methods that take into account labeling of neighbors when seeking to determine the most appropriate class for a pixel are said to be context sensitive, or simply context classifiers (Richards and Jia, 2006). Existing context classifiers can be usually summarized in four categories (Richards and Jia, 2006): (1) *Preprocessing:* In this method, the image is preprocessed via spatial filters or more advanced texture analysis algorithms before classification takes place in order to extract spatial features (e.g. Gong and Howarth, 1990, 1992; Binaghi et al., 2003). Typically, local spectral and spatial information is used to divide the image into a number of homogeneous objects composed of adjacent pixels with the similar characteristics (i.e. employ an image segmentation). Early on, Kettig and Landgrebe (1976) presented the geo-object based classification method (OBCM) through extraction of homogeneous objects before classification. A series of studies followed to explore further OBCM and have been proved successful in a number of recent applications (e.g. Blaschke and Hay, 2001; Benz et al., 2004; Hay and Castilla, 2008; Johansen et al., 2010; Lizarazo and Barros, 2010). (2) *Postprocessing:* Instead of processing an image before classification, a post-classification filtering method performs spatial context analysis on the classification results. Local spectral and spatial information is integrated by examining the labeling of neighboring pixels in the intermediate classification map using a spatial mask. The label of the center pixels within the spatial mask might be changed to the label most represented in the spatial mask (Townsend, 1986; Barnsley and Barr, 1996; Kim, 1996; De Voorde et al., 2007; Chormanski et al., 2008; Mas et al.,

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2010). (3) *Probabilistic label relaxation:* In this method, local spectral and spatial information is integrated in the form of probabilities within a spatial mask for each pixel. The probabilities of each pixel are adjusted according to the labeling of neighboring pixels within a spatial mask and are used in the classification (Gong and Howarth, 1989; Richards and Jia, 2007; Yi et al., 2007; Reigber et al., 2010). (4) *Markov random fields* (Dubes and Jain, 1989; Khedama and Belhadj-Aissa, 2004; Tso and Olsen, 2005; Tolpekin and Stein, 2009): Similar to the probabilistic label relaxation method, the Markov random fields method integrates local spectral and spatial information by looking into the probabilities of adjacent pixels. However, this method measures the prior probability using Bayes' theorem to maximize the global posterior probability in order to incorporate the spatial context information.

The classification model adopted in this paper also incorporated contextual information. The process was divided into a priori and a posteriori classifications, where classified pixels from the a priori method assisted in the classification of the leftover pixels handled by the a posteriori method. Distinct from previous context classification methods, the pixels classified through the a posteriori classifier were neither previously labeled nor had a probability assigned to them, instead they were classified on the fly. Furthermore, a significant difference between this paper and our prior work (Luo and Mountrakis, 2010) is that this model integrated spectral and spatial information exclusively from a local neighborhood to identify unclassified pixels, while all other surrounding pixels at larger scale were ignored. The working hypothesis is that already classified neighboring pixels will contain enough class information of spectral reflectance (similar materials) and spatial structure. Also, by ignoring information from the entire scene we will limit misclassifications. Part of our investigation focused on neighborhood type and size identification.

In order to derive partially classified results, a hybrid classification structure comprised of a series of steps was proposed. Hybrid classifiers have demonstrated potential for higher classification accuracy over single classifiers (Steele, 2000; Liu et al., 2002, 2004; Coe et al., 2005; Mountrakis et al., 2009; Franke et al., 2009). The objective of this research was to improve impervious surface classification accuracy by integrating contextual information in a hybrid classification model. To assess the performance of this novel classification model, two Landsat images from 2001 and 2006 covering central New York were used, respectively.

2. Methodology

A hybrid multi-process classification model that integrated multiple classifiers was used as the classification model for this paper (Fig. 1). It was a progressive process comprised of multiple steps. In each step, parts of the dataset were classified while the remaining portions of the dataset were forwarded to subsequent steps. Initially, an a priori classifier was used to derive partially classified results. After the partially classified results were processed by a majority filter, an a posteriori classifier was implemented to identify the remaining unclassified pixels. This a posteriori classifier integrated spectral and spatial information of the partial classification results from the previous two steps (a priori and majority filter) as contextual information. This paper focuses on the a posteriori classifier and assesses potential benefits and tradeoffs of the method.

2.1. A priori classifier

The purpose of the a priori classifier was to produce a partially classified image that would act as the basis for subsequent classification steps. Any classification algorithm could be used as the a

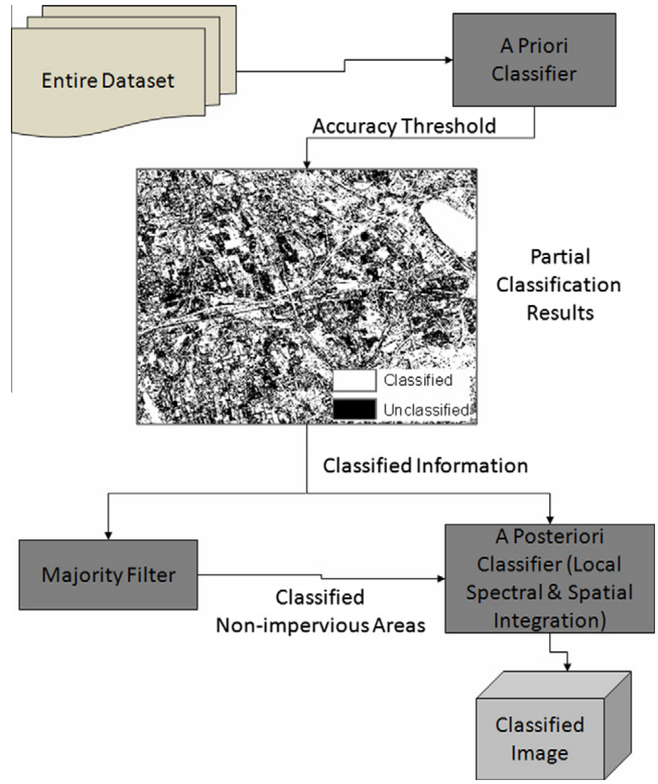

Fig. 1. The framework of the hybrid multi-process classification.

priori classifier, the only constraint was that their classification results should be able to provide a continuous range of accuracies. To determine the portion of partial classification results, a threshold was applied on the a priori classifier to ensure that the extracted pixels were classified with certain accuracy. The accuracy threshold was set up based on the calibration dataset and balanced the tradeoff of sufficient yet accurate partial results. Higher amount of already classified pixels (partial results) could reveal additional contextual information for later steps. However, as the classified pixel amount increased the classification accuracy decreased which could lead to additional but erroneous contextual information for the subsequent classifiers. Multiple thresholds were tested to identify the optimal for a given image problem, a process investigated in prior work (Luo and Mountrakis, 2010; Mountrakis and Luo, 2011).

In this experiment, the multi-layer perceptron feed forward neural network structure trained with a back-propagation learning algorithm was adopted as the a priori classifier. One thousand different neural network architectures were trained using the Levenberg–Marquardt backpropagation learning algorithm and the one with the best overall accuracy on the calibration dataset was identified (more on training datasets in Section 2.4). The input layer contained six nodes corresponding to the six Landsat ETM+ image bands (blue, green, red, near IR and two mid IR bands). Each node at the output layer represented one class (therefore a total of two nodes for impervious and non-impervious class, respectively) and was comprised of a logistic function. The range of each output node was continuous between 0 and 1. The node number in hidden layers was randomly selected during the training process of the 1000 architectures: between 6 and 15 for the first hidden layer and from 0 to 9 for the second hidden layer. The activation functions for the hidden layers were tangent sigmoidal functions. In order to translate a predetermined accuracy threshold to an output node threshold of the selected best neural network, each node