AUTOMATIC MAPPING OF LINEAR WOODY VEGETATION FEATURES IN AGRICULTURAL LANDSCAPES

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ABSTRACT

Development of automatic methods for agricultural mapping and monitoring using remotely sensed imagery has been an important research problem. We describe algorithms that exploit the spectral, textural and object shape information using hierarchical feature extraction and decision making steps for automatic mapping of linear strips of woody vegetation in very high-resolution imagery. First, combinations of multispectral values and multi-scale Gabor and entropy texture features are used for training pixel level statistical classifiers for characterizing individual trees and tree groups with respect to their surroundings. Then, decisions based on object level texture features and morphological shape analysis provide the final detection of woody vegetation having a linear structure. Experiments on QuickBird imagery from different sites show that the proposed algorithms provide good localization of linear strips of woody vegetation in different landscapes.

Index Terms— Vegetation mapping, hedge detection, multi-scale texture analysis, morphological shape analysis

1. INTRODUCTION

Agricultural practices play an important role in both environmental management and economical development of nations. In the European Union, cross-compliance standards and programs to enforce the regulation of such standards oblige farmers to play active roles in landscape and habitat maintenance in addition to managing their farms in sustainable ways. Development of automatic and robust remote sensing techniques for agricultural monitoring and change detection studies in order to help enforcing these standards and regulations has become an important research problem. The goal of this research study is to develop automatic methods for detailed mapping of target landscape features in very high-resolution imagery to produce a layer for monitoring of change.

This work was supported in part by the European Commission Joint Research Centre contract 253352 and TUBITAK CAREER grant 104E074.

The target objects of interest in this paper are "linear strips of woody vegetation" separating agricultural fields. These objects include hedges/hedgerows defined as a row of bushes or trees planted closely to form a boundary between pieces of land or at the sides of a road, and riparian vegetation along river or stream margins. These objects are important biological and ecological components of the environment where they serve many functions including providing field boundaries, animal habitats, windbreaks, erosion control and contributing to landscape ecology and biodiversity [1].

Classification of land cover has traditionally been performed using pixel level processing with mainly statistical tools in a multi-class setting. However, accurate delineation of individual trees or tree groups is not necessarily very accurate when the goal is to classify the whole land cover. Furthermore, finding sufficient number of examples for each class may not always be possible, and these classifiers may not generalize well for a large number of classes, especially when some of them have large variations in appearance. Alternatively, identification of green vegetation by thresholding specific spectral features such as the normalized difference vegetation index (NDVI) [2] considers only the spectral properties of individual pixels and does not take into account spatial and contextual information. Another method that is widely used for detecting pre-defined objects is template matching where detection is performed by moving the template over the image and evaluating the match at each location using a similarity measure such as correlation [3]. However, these templates are often fixed in terms of size, shape and intensity, and cause the detection algorithm to have problems regarding invariance to scale, rotation and illumination. Finally, generic object-based classification is also not suitable here because a holistic analysis requires an image-wide prior segmentation, but accurate segmentation of very high-resolution images is still an unsolved problem.

Quackenbush [3] published a review of techniques for linear feature detection in images. Popular techniques include mathematical morphology, Hough transform, multi-resolution edge detection, template matching, dynamic programming for edge linking, and rule-based classification. Most of these techniques were developed for extracting roads. However, these techniques are not directly applicable to detection of linear strips of woody vegetation because they assume the existence of collinear and parallel line segments that constitute pairs of edges forming the boundaries of roads, whereas the textured agricultural regions often produce a lot of small line segments both within and along the boundaries, and the edges that can be detected along the boundaries of vegetation regions also show a lot of irregularities. Furthermore, rural linear features such as hedgerows and riparian vegetation often exhibit directional variation according to whether they follow natural boundaries such as streams and rivers, or whether they follow man-made linear objects such as roads, or whether they have been planted as separators between agricultural fields [4].

The detailed content of very high-resolution imagery and the large spatial coverage of such data sets require the development of new techniques for detection of individual predefined objects. In this paper, we propose algorithms that exploit the spectral, textural and object shape information using hierarchical feature extraction and decision making steps. The first step is the extraction of pixel-based spectral and textural features from input data (Section 2). Next, thresholds on spectral indices and discriminant functions trained on combinations of multi-scale texture features are used to select the pixels that may belong to targets of interest (Section 3). Then, connected components analysis on these pixels is used to obtain candidate objects, and object level texture and shape features are examined so that the objects can be labeled as target or are rejected (Section 4). Experiments on panchromatic and pan-sharpened multispectral QuickBird imagery from several European sites show that the proposed algorithms provide good localization of linear strips of woody vegetation (called hedges in the rest of the paper) in different landscapes.

2. FEATURE EXTRACTION

Spectral features can be used to distinguish green vegetation from the rest of the image. Texture features are useful for modeling pixel neighborhoods by separating areas that have similar spectral responses but different spatial structures. We observed that two types of textural characteristics are important: the arrangements of individual trees and the appearance of linear structures with respect to their surroundings. Hence, the following multi-scale texture features were considered.

Normalized difference vegetation index: The normalized difference vegetation index (NDVI) [2] is a simple but powerful measure for identifying photosynthetically active vegetation. NDVI, that is computed from the pan-sharpened multispectral data, was used to separate green vegetation from the rest of the land cover. We observed that, although it might not distinguish hedges from other types of vegetation, it was useful for eliminating linear man-made structures that could cause false alarms in the decision process.

Gabor features: Gabor features were extracted by applying a bank of scale and orientation selective filters [5] to the panchromatic band. In particular, 6 scales and 6 orientations were used with a resulting set of 36 bands. The scales used were designed to include both the fine texture of individual trees within a hedge and the coarse texture of hedges among agricultural fields. To obtain rotation invariance, the responses for all filters with different orientations at a given scale were combined using the pixelwise "max" operator.

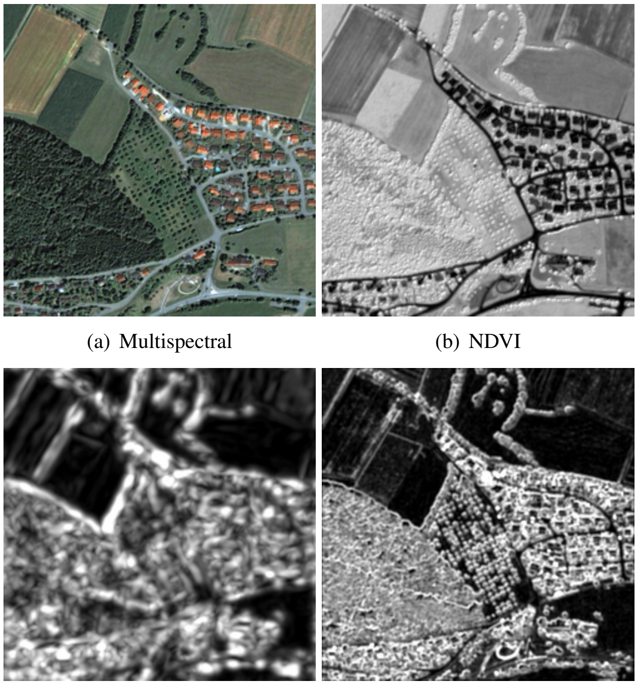
Entropy features: Another texture feature that was used to model the spectral variations within a neighborhood was the entropy. The entropy of the distribution of these variations within sliding windows were observed to give a high response over the tree covered areas. To emphasize the fine texture and the corresponding spectral variations, entropy was computed using the histogram of gradient orientations instead of raw pixel intensities. The contribution of each pixel in this histogram was weighted according to the corresponding gradient magnitude. Furthermore, to model multi-scale characteristics, the features were computed using rectangular windows with 6 different sizes and 4 orientations, and rotation invariance was obtained using the pixelwise "max" operator as in the Gabor case.

These texture features were selected because they not only describe image windows but are able to localize the structure of interest within these windows. In particular, using visual inspection, we observed that Gabor features were good at modeling the coarse texture of woody vegetation with respect to its surroundings, and the entropy features were good at modeling the fine texture of individual trees within the hedge structure. Example features are shown in Figure 1.

3. IDENTIFICATION OF CANDIDATE OBJECTS

After the features are extracted, the next step is to find the image areas that give high responses to these features so that they can be considered as candidate objects. We used a two-step decision process. First, a threshold on NDVI was used to separate green vegetation from the rest of the land cover. The threshold was selected so that there was no omission of any hedge structure. However, we observed that such thresholding could not distinguish hedges from other types of vegetation and kept many fields, large groups of trees and other vegetated areas in the output. On the other hand, the thresholding eliminated some linear man-made structures that gave high responses to the texture features.

Given the obtained vegetation mask, the next step is to identify candidate objects according to their texture characteristics. Manual labeling of image areas as woody vs. non-woody vegetation was used to generate the ground truth. A randomly selected subset consisting of 500,000 pixels collected from scenes from three different countries was used to train discriminant functions and another subset with the



(a) Multispectral (b) NDVI

(c) Gabor - scale 6 (d) Entropy - scale 1

Fig. 1. Example features for a 1000×1000 part of an image.

same number of pixels was used for validation. The learned discriminant functions were used to classify the pixels as belonging to woody vegetation or not. Different combinations of multispectral bands and texture features were studied with two different classifiers (Gaussian and mixture of Gaussians).

Table 1 shows the correct classification rates for different combinations. Among the features, combining multispectral bands with texture features performed better than using each type of features individually. However, comparing the combination of Gabor features with multispectral bands and the combination of entropy features with multispectral bands did not show any significant difference. Among the classifiers, the performance of the Gaussian classifier approached to that of the mixture of Gaussian classifier when a higher number of features was used. Among all combinations, the Gaussian classifier with multispectral and Gabor features gave the highest accuracy, and was used in the rest of the experiments.

After the discriminant function identified the pixels that could belong to targets of interest, connected components labeling of these pixels was used to obtain the candidate objects. Morphological opening and closing operations were used to eliminate small noise components and to fill small holes. Example classification results are shown in Figure 2.

4. DETECTION OF TARGET OBJECTS

Given the candidate objects, object level texture and shape features can be used so that the objects can be labeled as target or are rejected. Visual inspection in Section 2 and numerical

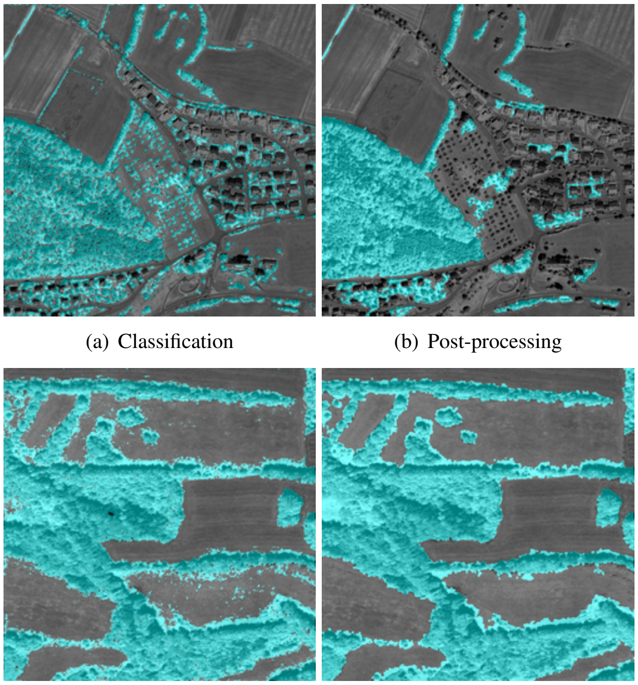
Table 1. Accuracy of classification for woody vs. non-woody vegetation using different feature combinations and classifiers (before morphological post-processing).

MS	Gabor	Entropy	Classifier	Accuracy (%)
X			Gaussian	89.36
X			Mix. of Gaussian	89.41
	X		Gaussian	79.22
	X		Mix. of Gaussian	85.61
		X	Gaussian	88.96
		X	Mix. of Gaussian	89.24
X	X		Gaussian	94.81
X	X		Mix. of Gaussian	94.40
X		X	Gaussian	93.73
X		X	Mix. of Gaussian	94.79
X	X	X	Gaussian	94.30
X	X	X	Mix. of Gaussian	94.52

results in Section 3 showed that Gabor features were good at modeling the coarse texture of woody vegetation with respect to its surroundings. To further eliminate some of the commission errors (e.g., groups of individual trees in an orchard), mean of the entropy features of the pixels of each object were computed as the statistical summary of the fine texture within that object. A threshold on these mean values was used to obtain a refined set of objects containing woody vegetation. Example results for this step are shown in Figure 3.

The final decision regarding the mapping of linear strips of woody vegetation (hedges) was done based on shape information. The shape information was extracted using morphological filtering. Several disk structuring elements with some being smaller and some being larger than the expected sizes of linear strips were constructed. Then, the hedges were extracted from the set of candidate objects using consecutive application of top-hat transforms and conditional dilations. The morphological top-hat transform is computed as the difference between the image and its opening. Therefore, it removes the image structures that cannot contain the structuring element used. The consecutive application of top-hat transforms aims to extract the objects having a width value within a given range of values that can be adjusted by the user. The conditional dilations aim to recover the effects of opening and extract the objects as they appear in the initial input.

Example detection results are shown in Figure 4. Since no object level ground truth was available, the performance of the final detection was evaluated by visual inspection. We observed that when the amount of commission errors caused by the pixel level classifiers during the identification of candidate objects was small, the shape analysis step could recover most of the hedges with good localization and very low degree of omission. The remaining commission errors were mostly due to other types of vegetation with a similar low-level texture as a hedge. We believe that additional texture features, shape measures and contextual models can provide further improvement of the detection performance.



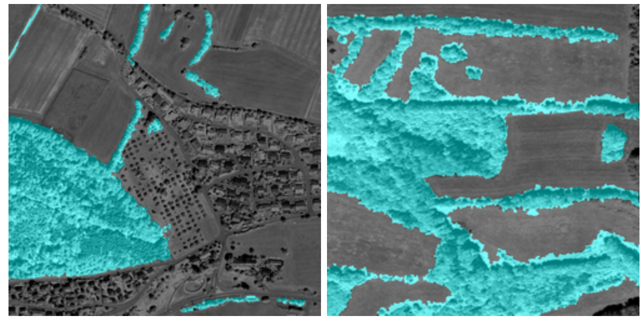
(a) Classification (b) Post-processing

(c) Classification (d) Post-processing

Fig. 2. Example results for classification and morphological post-processing for two 1000×1000 scenes from Germany (top row) and Czech Republic (bottom row). The image areas identified as woody vegetation are marked in color.

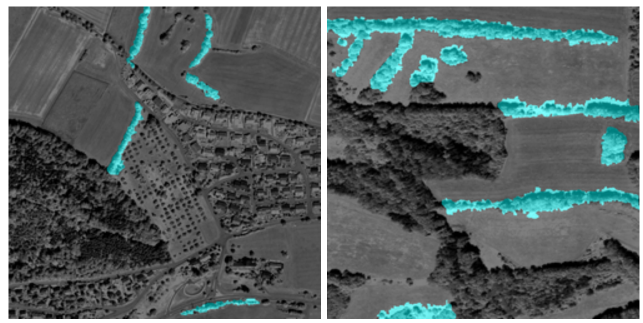
5. SUMMARY AND DISCUSSION

We described algorithms that exploited the spectral, textural and object shape information using hierarchical feature extraction and decision making steps for automatic mapping of linear strips of woody vegetation (hedges) in very high-resolution imagery. Detection of such specific target objects necessitates a multi-scale and multi-feature strategy as no single feature can achieve good localization performance when used individually. For example, vegetation indices and multispectral values gave a high response on the trees but missed the shadows and could not model the textural characteristics of hedges. Multi-scale texture features could characterize the fine texture of individual trees within the hedge structure as well as the coarse texture of woody vegetation with respect to its surroundings. Statistical classifiers trained on combinations of features and morphological post-processing by exploiting the shape information showed promising detection performance on different scenes.



(a) (b)

Fig. 3. Example results for object level thresholding based on entropy features.



(a) (b)

Fig. 4. Example results for final detection based on morphological shape analysis.

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