IMPROVING REMOTE SENSING-DERIVED LAND USE/LAND COVER CLASSIFICATION WITH THE AID OF SPATIAL INFORMATION

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ABSTRACT

Most fundamental per-pixel classification techniques group pixels into clusters based on their spectral characteristics. Since various terrestrial objects may exhibit similar spectral responses, the classification accuracies of remote sensing derived image-maps is often reduced. This study focuses on using the shape index of detected ground objects to resolve some of the spectral confusions which occur when pure per-pixel classification algorithms are applied. First, homogeneous areas were identified by using an edge detection algorithm. Second, a stratification procedure divided the image into two strata based on the shape index of patches. One stratum was composed of patches with regular shapes and large sizes, such as agricultural fields and some wet meadows. The other stratum was composed of highly fragmented patches, including urban areas, roads, and riparian vegetation. By stratifying the image, the classes which frequently caused mixed clusters, such as grassy surfaces in urban areas and crop fields, wet fields and riparian forests, were assigned to different strata, thus reducing the possibility of spectral confusion. Third, a spectral classification algorithm was applied to the two strata separately to derive the land cover information for each layer. Finally, the two classifications were merged to produce the final land use/land cover map of the study area.

INTRODUCTION

Multispectral classification techniques have been used for a variety of applications, such as land use/land cover mapping, crop classification, wetland change detection, and landscape diversity measurements. Most of the fundamental classifiers such as ISODATA, sequential clustering, and maximum likelihood classification, group pixels into clusters based on their spectral characteristics. However, due to the spectral sensitivity of remote sensing instruments and the material properties of terrestrial features, pixels belonging to different classes may exhibit inherently similar spectral properties (Gurney and Townshend, 1983). For example, it is not surprising to find that grassy surfaces (e.g., lawns, parks, etc.) within an urban area are often misclassified as agricultural fields. In other cases, bare fields may be confused with concrete surfaces in urban areas, or that riparian woodlands have been mixed with wet agricultural fields when per-pixel spectral classification techniques are used.

Human interpreters can resolve most of these confusions since they possess a comprehensive knowledge of image tone, texture, pattern, association, shape size, position, and other related characteristics of various features (Gurney,1981). Consequently, visual interpretation often achieves a much higher accuracy than automatic digital classifiers though it is laborious and time-consuming process. Innovative models have, therefore, been developed to take into account spatial information in addition to spectral information, to aid in classification (Argialas, 1990). These spatial classifiers often consider such aspects as image texture, pixel proximity, feature size, shape, direction, repetition, and context for improving the classification of an image (Lillesand and Kiefer, 1994).

Spatial information inherent in an image itself can be extracted to assist the spectral classification process. Various kinds of spectral information have been used in pre-classification segmentation, post-classification labelling, or as additional layers input into a statistical classifier. Gurney (1983), used the relative locations of clouds and shadows to successfully separate cloud shadows from spectrally similar water surfaces. Johnsson (1994), improved the spectral classification results by reassigning segments according to a set of decision rules based on size and neighborhood. In another study, Fung and Chan (1994) used the spatial composition of spectral class (SCSC) within a moving window to label pre-classified spectral classes for deriving land use/land cover characteristics. Based on the SCSC ranges, the authors were able to separate water, high density urban land, low density urban land, bare areas, and grassy surfaces. An edge detection segmentation method along with a knowledge based classification that took into account the contextual, textual, and spectral information of segments was developed by Moller-Jensen (1990) to classify an urban area. The author concluded that an expert system-based classification approach produced improved results over traditional classification techniques.

This study focuses on using a stratification process to avoid some of the spectral confusions which occur when pure per-pixel classification is used. A combination of spectral and spatial pattern recognition techniques was used for classifying the land use/land cover of an image. A directional first-differencing algorithm was applied on the original image to highlight edge information. Relatively homogeneous areas were clumped based on the network of edge features, and each homogeneous patch was assigned to either the simple-shape group or the fragmented group, using its shape index. Spectral classification was performed on these two groups separately, and the two classified image-maps were merged to produce a composite classification of the study area.

STUDY AREA

The study area for this project lies in the central Platte River valley. It is comprised of portions of Merrick and Polk counties in Nebraska. A subset of the Landsat Thematic Mapper (TM) image, Path/Row 29/31, acquired on 19 August 1992 was used to illustrate the methodology of the knowledge-based land use/land cover classification of the Platte River flood plain (Figure 1). In the study area, agricultural land dominates the landscape, with corn, sorghum, and soybean being the major crops. Remnants of natural grasslands are found only on the flood plain bluffs, while wet meadows are distributed along the Platte River channel and other small streams. Woody vegetation, which requires more moisture than grasslands is a composite of riparian forests and wetland shrubs and is formed mainly along the stream channels. In sum, natural vegetation cover is extremely fragmented due to the intensive agricultural and other human activities prevalent in this region.

METHODOLOGY

The classification strategy discussed in this paper involved a three-step process. First, homogeneous areas were identified using an edge detection technique on the raw image data, whereby, linear features or edges were detected to isolate these areas. Contiguous non-edge pixels were grouped as a unit. Second, these homogeneous units were stratified into two groups based on their shape index values . One group included agricultural fields and a part of large wet meadow parcels, while the other consisted of highly fragmented features, including urban areas, roads, and riparian vegetation. Finally, a per-pixel spectral classification algorithm was applied to the two groups separately. Pixels were labelled into one of the following eight categories: agricultural, water, forests, wetland shrubs, wet meadows, grassland, urban/roads, and bare.

Identification of Homogeneous Areas

A digital image is a complex of points (i.e., single pixels), and patches (i.e., connected sets of pixels with some uniform property such as grey level or texture) (Argialas, 1990). An edge detection method modified from the directional first differencing algorithm was developed to detect border pixels of homogeneous areas (or patches) and linear features. Every land patch was assigned an unique value to evaluate it as a whole unit in order to facilitate the subsequent measurement of the shape index. This measurement was essential to the stratification of the image.

The first differencing algorithm is designed to emphasize edges in image data (Lillesand and Kiefer, 1994). It is a procedure that systematically compares each pixel in an image to one of its immediate neighbors as follows:

P	H
V	D

P - Primary pixel being processed
H - Horizontal neighbor
V - Vertical neighbor
D - Diagonal neighbor

Horizontal first difference = $BV_P - BV_H$ (1)
Vertical first difference = $BV_P - BV_V$ (2)
Diagonal first difference = $BV_P - BV_D$ (3)
BV = brightness value of pixel

In this study, both horizontal and vertical first differences were computed using TM bands 2, 3, and 4. The differences of the brightness values (BVs) between one pixel and its neighbors can be negative, positive, or zero. However, since the multi-band differencing algorithms (equations 4 and 5) require absolute values, the signs of the differences are removed.

Horizontal first difference = $|DN_{P2}-DN_{H2}| + |DN_{P3}-DN_{H3}| + |DN_{P4}-DN_{H4}|$ (4)
Vertical first difference = $|DN_{P2}-DN_{V2}| + |DN_{P3}-DN_{V3}| + |DN_{P4}-DN_{V4}|$ (5)
where: 2, 3, and 4 represent TM bands 2, 3, and 4 respectively.

If the directional first differencing of a pixel is larger than or equal to the threshold value of 10, in either direction, the pixel is selected as an edge pixel, otherwise it is ignored. The threshold value was determined by experimenting with different values, and examining their effects on the image. Unfortunately, this is not a universally applicable value. An appropriate threshold value should be determined by the users since it may vary in different images.

All edge pixels were assigned a value of 1 in the output image, and all non-edge pixels were assigned a value of 0. Based on this output, contiguous groups of pixels with zero difference values were clumped into patches. Each patch was a relatively homogeneous area and was assigned an unique value so as to be treated as an independent unit in shape measurement.

Essentially, the detected edge pixels make up a boundary network which manifests homogeneous areas (Figure 2). Obviously, some pixels are the borders of fields, but they are also a part of the adjacent patch. For example, if there are two adjacent fields, the boundary pixels between them will be detected as edges (Figure 3). They are basically part of the field on the left side of or above them, and can be extracted and assigned back to the patches they belong to. If the neighboring pixel on the left, or the neighboring pixel above an edge pixel is not an edge pixel, it would indicated that the edge pixel is not significantly different from this neighbor and should therefore, belong to the same patch. These border pixels only served as edges temporally for the identification of homogeneous areas, but they can be reassigned back to the appropriate patches. This edge detection technique has an advantage over other edge detection methods (e.g., high-frequency filtering and texture measurements), which cannot differentiate linear features and land borders, and therefore, often cause "edge errors".

Pre-classification Stratification

Stratification is usually performed before per-pixel classification in order to separate cover types with inherent spectral similarity. The geometric appearance of an object (i.e., its shape), is an important element of pattern recognition. In this project the shape index of each feature was computed using the ratio of perimeter to area algorithm. Implementing this step resulted in the stratification of the image into a stratum of simple, regular shape patches and a stratum of complex-shaped patches.

In many parts of the U.S., where the terrain is smooth, agricultural fields often have regular shapes and very simple perimeters, and therefore, a low perimeter to area ratio. Conversely, urban areas, grasslands, and natural woody vegetation have irregular shapes and complex perimeters, and consequently, yield high shape index values. In the case of some wet meadows, which have large size and smooth texture, medium shape index values were derived. All patches were sorted into two groups. The first group was comprised of patches with regular shape and large size, including agricultural fields with crops, bare fields, and some wet meadows. The second group was comprised of fragmented patches with complex shapes, and included urban areas, roads, streams, upland grasses, wetland shrubs, and forests. Detected edges were the most irregular and complex features, and were accordingly assigned to the fragmented group.

Once this stratification was completed, the classes which were hard to separate based on their spectral characteristics, such as discrimination between grassy surfaces in urban areas and crop fields with low infrared spectral reflectance, or wet fields and riparian forests, or upland grasses and wet meadows, etc., were assigned to different groups, thus reducing the possibility of spectral confusion. Each group of land patches was used to create a mask to extract the corresponding areas from the original image. Consequently, two image-strata were formed. One comprised of a highly fragmented stratum, while the other was a low fragmented stratum.

Spectral Classification

Each image-stratum was classified independently. TM bands 2, 3, 4, and 5 were used to extract 50 clusters from the highly fragmented stratum, using a self-iterative, unsupervised clustering algorithm. The clusters were assigned in feature space using the maximum likelihood rule. Each cluster was grouped into a land use/land cover category by overlaying it on a false-color composite of the image, and delineating its respective location on the red-infrared (TM bands 3, 4) scatterplot. The methodology was also applied to classify the low fragmented stratum. However, only TM bands 3, 4, and 5 were used, since an examination of the TM band 2 histogram for the low fragmented stratum revealed a narrow range of BVs. Such uniformity of BVs makes it difficult to extract reliable clusters and therefore leads to poor classification results.

Once the low fragmented stratum was classified, the two classifications were merged to produce a final land use/land cover image-map with eight categories: water, wetland shrubs, forests, wet meadows, grassland, agricultural fields, urban, and bare fields (Figure 4). It is evident from Table 1 that agriculture occupies a substantial portion of the landscape (nearly 51%), while natural grasslands, wetlands, and forests comprise only 42% of the landscape. The ratio of the natural vegetation land area is deceptive, since much of the grassland included in this image interpreted consists of fields that are used for grazing purposes or those that have left been fallow. This is because the central Platte River Valley has undergone significant transformation over the last century. Most of this has been due to agricultural and development activities. These activities have led to a reduction in the extent of native vegetation and the fragmentation of their remnants (Narumalani et al., 1995). From the perspective of conserving natural resources, it is important to conserve what remains and implement schemes that are compatible with existing land use activities. Future agricultural activities must be carefully monitored to minimize their impact on the remaining natural vegetation of the area.

Table 1. Land Cover Classification of the Study Area.

Class Name	Area (ha)	Percent (%)
Water	532.59	2.2
Wetland shrub	3208.31	13.1
Forest	476.39	1.9
Wet meadow	2336.84	9.6
Agriculture	12410.9	50.8
Grassland	4335.38	17.8
Urban	174.15	0.7
Bare/Fallow	941.64	3.9

SUMMARY AND CONCLUSIONS

The approach discussed in this paper identified homogeneous areas by using the directional first-differencing method. Border pixels could be extracted and assigned back to the patch to which they belonged. The critical step in this edge detection method was thresholding. Determining the threshold was an experimental process affecting the quantum of the edge bias for the analysis. If the threshold is too small, non-edge pixels will be included. Conversely, if it is too large, edges may not be detected, neighboring patches may join, and hence interfere with the shape measurements and the subsequent stratification. Another important aspect related to the effectiveness of the edge detection technique is band selection. In this study, Landsat TM bands 2, 3, and 4 were used due to the following reasons. TM band 4 allows biomass detection and differentiation, while bands 2 and 3 clearly show roads, urban areas, and streams, which are a major component of the border features. A false-color composite (TM bands 2, 3, 4 = RGB) shows the best representation of border features.

In the central Platte River valley study area, crops are usually planted in uniform, distinct fields, often with a single crop to a field. This farming pattern permitted an effective stratification and aided to the spectral classification. However, in many regions of the U.S., and the world, crops are planted in very small fields due to topographic, cultural, or landscape characteristics. Consequently, the geometric differences between natural cover and agricultural fields might be undetectable, and other more effective methodologies may need to be developed.

Stratification involves a division of the study scene into smaller areas or strata based on some criterion or rule so that each stratum can be processed independently (Hutchinson, 1982). The purpose of stratification in this research was to separate different features which cause confusion due to their spectrally similarity. The stratification divided the original image to two strata, but did not alter its original BVs. The stratification results are effective, except for a few small or irregular agricultural fields which were assigned to the high fragmented stratum. However, such fields or patches still can be classified into their appropriate land use/land cover classes if their spectral values do not deviate too far from the class means. A visual comparison of the original image data with the classified image-map showed that the methodology described in this paper was effective in resolving much of the classification confusion, especially between agricultural fields and urban grassy surfaces, or riparian forests.

Spatial information, which is implied in the image, can be a significant ancillary data source for digital classification improvement. Its extraction from digital imagery, especially high resolution images such as those acquired by the Landsat TM and SPOT sensor systems, would greatly improve image classification if proper strategies are used.

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Figure 1. Landsat Thematic Mapper (TM) image subset of the Platte River valley study area, acquired on 19 August 1992, band 3.

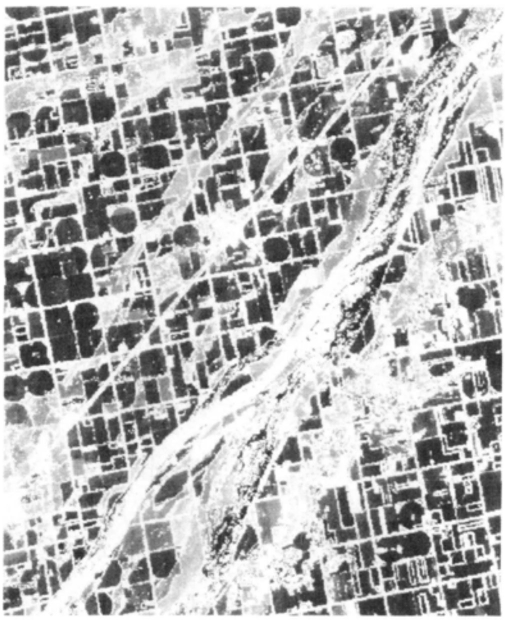

Figure 2. Results of the directional first differencing algorithms overlaid on TM band 3.

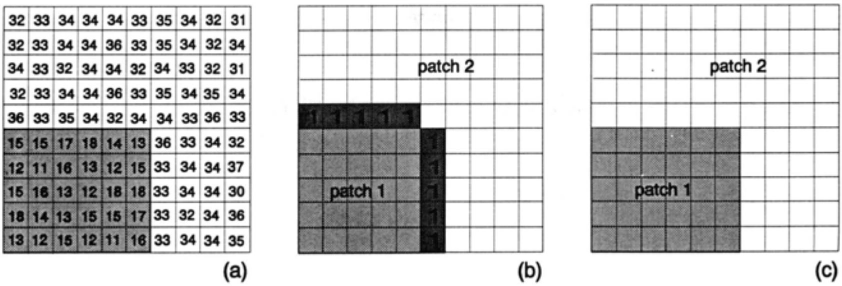

Figure 3. Edge detection and modification process: (a) a single-band sample of the original digital image data, (b) patches clumped based on edge information, and (c) border pixels assigned to their respective patches.

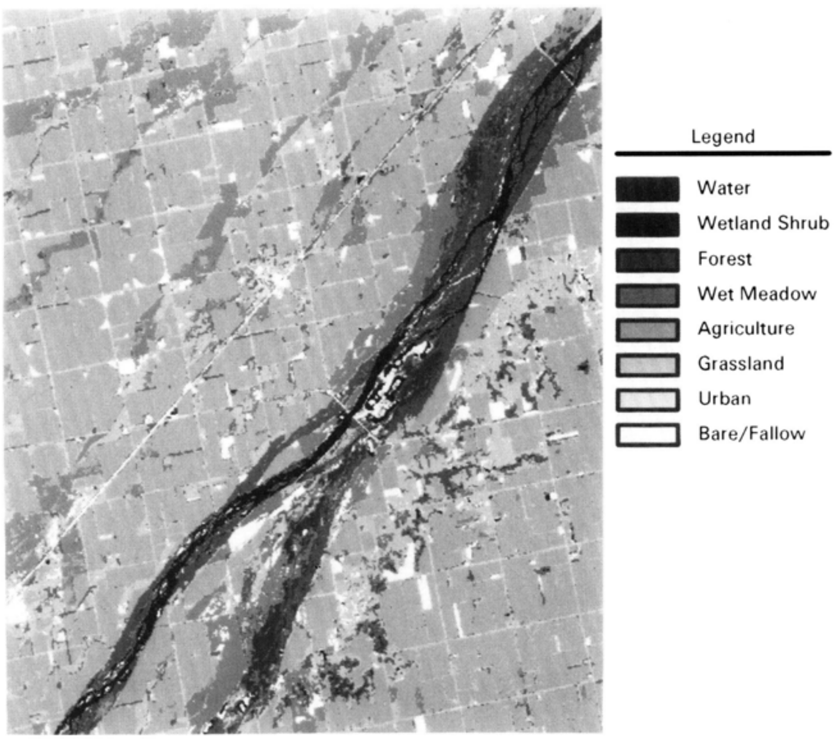

Figure 4. Final land use/land cover classification derived after application of the stratification methodology.