MULTISPECTRAL DATA CLASSIFICATION BASED ON SPECTRAL INDICES AND FUZZY C-MEAN

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1. INTRODUCTION

Numerous applications make use of data on land use and land cover (LULC). Given their importance and use, land cover data is assumed to be readily available or trivially acquired for a given landscape. Unfortunately, this is often not the case. LULC data at hand are often out-of-date, inappropriate for a particular application [1], or contain other difficulties. Thematic mapping of remotely sensed data is typically some form of image classification. Supervised image classification is generally achieved by either visual or computer-aided analysis, including classical statistical algorithms such as maximum likelihood, evidential reasoning, and artificial neural networks. One major limitation to the use of conventional supervised classification techniques for mapping land cover is that they were developed for the classification of classes that may be considered to be discrete and mutually exclusive, and assume each pixel to be pure, that is comprised of a single class. As a pixel is an arbitrary spatial unit, it may represent an area on the ground which comprises more than one discrete LULC class. This problem will be more apparent with coarse spatial resolution data. Fuzzy classification techniques can, however, accommodate the partial and multiple class membership of mixed pixels, and be used to derive an appropriate land cover representation. In this work, we propose the use of cascaded fuzzy C-mean classifiers for LULC classification. The main contribution to LULC classification is the use of spectral indices, and cascaded classifiers for the classification of remotely sensed data.

2. METHODOLOGY

Different materials are discriminated by wavelength-dependent absorptions which are known as spectral signatures. Detailed information about how individual elements in a scene reflect or emit electromagnetic energy increases the probability of finding unique characteristics for a given element which allows for better distinction from other elements in the scene [2]. Basically, several studies have derived band ratios or spectral indices which are useful for emphasising certain spectral features. These ad hoc transforms can be used to distinguish between different vegetation within a mosaic of other land uses (e.g. NDVI) [3]. [4] introduced the Soil Adjusted Vegetation Index (SAVI) in order to minimize the soil darkness influence. Based on a constant soil adjustment factor, L. SAVI minimizes the effect of soil background reflected radiation. [5] developed the Brightness Index (BI), which applies the reflectance values in two visible bands green (G) and red (R), and the NIR band to calculate the soil brightness. Given the goal of mapping LULC, it was believed that it would be possible to develop spectral indices for differentiating between the various LULC types directly from their respective spectral signatures. This would have the advantages of improving the ability of a classifier to objectively derive LULC products. In the current work, we introduce two novel spectral indices BRED and BNIR to serve as new features to be used in the classification procedure:

$$BRED = (R - B)/(R + B); BNIR = (NIR - B)/(NIR + B) \tag{1}$$

A fuzzy C-mean classifier was then used to classify the remotely sensed data using the developed spectral indices. Fuzzy methods have previously been used to classify remotely sensed data sets [6], and offer some advantages over other classification methods. The output of the fuzzy classification is a map showing the LULC classes on a continuous scale from 0 to 100%.

The hierarchical framework implemented within the current classification system (Fig. 1) is used to provide a base map of the LULC types for an input Landsat/Spot/Ikonos/Quickburd images. The LULC descriptions are as follows: (1) High density (HDV) canopy cover $>50\%$ and includes vegetation with high leaf area index (LAI); (2) Low-density canopy (LDV) cover ($<50\%$), this class refers to the area with sparse fragmented vegetation including vegetation with low LAI; (3) Bare Land (BS) refers to area of exposed soil with very little or without vegetation coverage including paths; (4) Rocky soil (RS) includes mines and non-agricultural soil; (5) Man-made objects (MM) cover Buildings and roads; and (6) Shadows (SHAD).

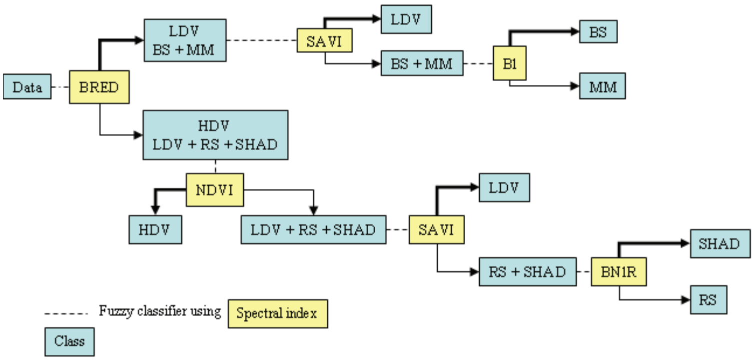

Fig. 1. Cascaded Fuzzy classifiers.

3. EXPERIMENTAL RESULTS

The following figure illustrate the obtained results using the proposed method on an input IKONOS images.

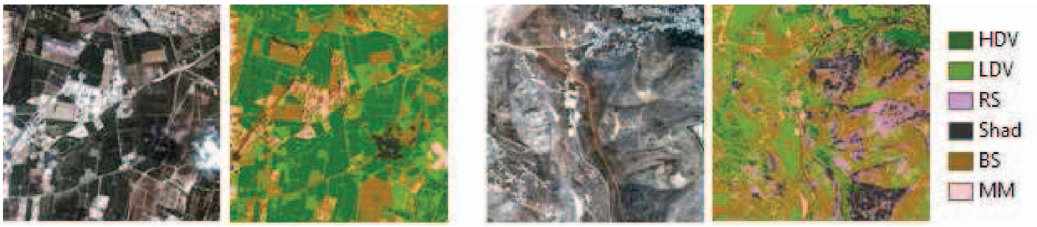

Fig. 2. Example of original images and their corresponding Base maps.

The proposed procedure has been assessed by calculating the confusion matrix. The maps of the maximum class memberships and the confusion matrix show that most of the area has been allocated unambiguously to a single class. Moreover, the obtained results shows the capability of the selected features to distinguish between the different LULC classes.

4. CONCLUSIONS AND FUTURE WORK

In this paper we proposed a classification approach which allows a fast landcover classification using spectral indices and cascaded fuzzy classifiers. Future research into the application of this methodology with different resolutions, quality image data with varying spectral bands and additional spectral indices may increase the accuracy of the classification of LULC.

5. REFERENCES

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