DISTRIBUTED LAND USE CLASSIFICATION WITH IMPROVED PROCESSING TIME USING HIGH-RESOLUTION MULTISPECTRAL DATA

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ABSTRACT

Image classification techniques can be applied to a geographical image to obtain its land use characteristics. Multispectral and high-resolution remote sensing images are able to provide sufficient information for a more accurate segmentation, nevertheless, the classification algorithms applied to images with high spatial resolution requires many computational cycles, even for modern computers. This paper explores the effectiveness of a novel approach developed for supervised segmentation and classification of high-resolution remote sensing images using distributed processing techniques to improve the computational time required. This is referred to as the distributed pixel statistics method. Examples of remote sensing signatures extracted from real world and high-resolution remote sensing images are reported to probe the efficiency of the developed technique.

Index Terms **—** Image Classification, Remote Sensing, Statistics, Distributed Processing

1. INTRODUCTION

Considerable progress has been made generally in the application of remote sensing techniques to both research and operational problems for urban planning and natural resource management. Modern applied theory of image processing for urban planning and natural resources management is now a mature and well developed research field, presented and detailed in many works ([1] thru [4] are only some indicative examples).

Although the existing theory offers a manifold of statistical techniques to tackle with the particular environmental monitoring problems, in many applications areas there still remain some unresolved crucial theoretical and data processing problems.

One of them is particularly related to the extraction of physical characteristics (e.g., water, land cover, vegetation, soil, humid content, and dry content) for applications in natural resources management (modeling and planning).

The development of a novel tool for supervised segmentation and classification of remote sensing signatures (RSS) from multispectral remote sensing (MRS) imagery is based on the analysis of pixel statistics.

Due to the large size of the high-resolution images, the use of distributed processing techniques is applied to improve the time required for the classification process, and is referred to as the distributed pixel statistics (DPS) method.

2. MULTISPECTRAL IMAGING

Multispectral imaging is a technology originally developed for space-based imaging. MRS images are the main type of products acquired by remote sensing radiometers. Usually, MRS systems have from 3 to 7 radiometers; each one acquires one digital image (also called scene) in a small band of visible spectra, ranging 450 nm to 12,500 nm [5].

The wavelengths for the spectral bands are defined as follows (the values are approximated, exact values depends on the particular MRS instruments [6]):

1) Blue: 450-520 nm.
2) Green: 520-600 nm.
3) Red: 600-690 nm.
4) Near-Infrared: 750-900 nm.
5) Mid-Infrared 1: 1,550-1,750 nm.
6) Mid-Infrared 2: 2,080-2,350 nm.
7) Thermal-Infrared: 10,400-12,500 nm.

For different purposes, combinations of spectral bands can be used. Most commonly, they are represented with red (R), green (G) and blue (B) channels (traditional photography), and are referred to as True-Color remote sensing images [5].

3. SPOT-5 IMAGES

SPOT Imagery (from its French acronym “Système Pour L’Observation de la Terre”) is the worldwide distributor of geographic information products and services derived from the SPOT Earth observation satellites. A SPOT satellite image is a view of the Earth seen through one of the satellite’s high-resolution imaging instruments. The technical characteristics of each instrument determine the resolution and spectral mode of the image. The acquired image is then processed to suit users’ requirements in terms of geographic information. It is delivered in a standard format able to be integrated directly in current geographic information software packages [7].

The images used for this research are provided by SPOT-5 through its Mexican office SEMAR (from its Spanish acronym “Secretaría de Marina”) under the ERMEXS program (from its Spanish acronym “Estación de Recepción México de la Constelación SPOT”) [8]. The spatial resolution of the images is 10m (spectral mode Hi) for a *6,000x6,000* pixels image, and the spectral resolutions (3 spectral bands) corresponds to the following:

1) B1 – Green (G): 520-600 nm.
2) B2 – Red (R): 600-690 nm.
3) B3 – Near-Infrared (I): 750-900 nm.

4. DISTRIBUTED PIXEL STATISTICS METHOD

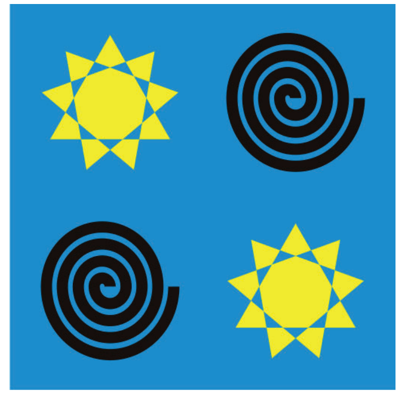
The distributed pixel statistics (DPS) classification rule is computationally simple, is based on the weighted pixel statistics method (WPS) but oriented to distributed processing to improve computational time consumption. An extensive study of the WPS method was performed in [9] to probe that the accuracy obtained with this classification process is more efficient (both qualitatively and quantitatively) compared with other more computationally intensive algorithm [6]. The DPS algorithm is characterized by the mean and variance values of the geographical signatures to be classified (defined as classes) and the Euclidean distances based on the Pythagorean theorem.

The training data for class segmentation requires the number of signatures to be classified (c); the mean matrix $\mathbf{M}$ ($c\times c$ size) that contains the mean values μ_{cc}: ($0 \leq \mu_{cc} \leq 255$, gray-level) of the classes for each multispectral band of the image; and the variance matrix $\mathbf{V}$ ($c\times c$ size) that contains the variances of the classes for each multispectral band. The matrixes $\mathbf{M}$ and $\mathbf{V}$ represent the weights of the classification process. Next, the image is separated in its spectral bands (G, R and I) and each (i, j)-*th* pixel is statistically analyzed calculating the means and variances from a neighborhood set of *5x5* pixels for each GRI band, respectively.

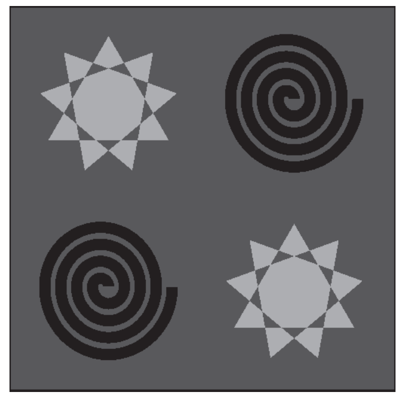
To compute the output of the classifier, the distances between the pixel statistics and the training data is calculated using Euclidean distances based on the Pythagorean theorem for means and variances, respectively, and employing distributed processing for time improvement. The decision rule used by the DPS method is based on the minimum distances gained between the weighted training data and the pixel statistics. Figure 1 shows the detailed processing structure of the DPS classifier.

5. VERIFICATION PROTOCOLS

To analyze the qualitative performance of the DPS technique, a multispectral test image is used. Figure 2(a) show the test image, containing three different regions (in yellow, blue and black colors) with a different pattern. Figure 2(b) show the DPS classification result.



(a) Test image.



(b) DPS classification for 3 classes.

Figure 2. Qualitative analysis of the test image.

6. SIMULATION EXPERIMENT

In the simulation results, a MRS image is used for RSS classification using the DPS method. Three level of RSS are selected for this particular simulation process as:

– RSS relative to the humid zones of the MRS image.
– RSS relative to the dry zones of the MRS image.
– RSS relative to the wet zones of the MRS image.
– Unclassified zones of the RSS map.

Figure 3(a) shows the MRS high-resolution (spatial resolution of 10m, *6,000x6,000* pixels, approximately *60x60* kilometers) and multispectral image (3 GBI spectral bands) in TIFF format, corresponding to the “Valles” region of the State of Jalisco in Mexico [8], [10].

Figure 3(b) shows a detailed section of the high-resolution image, corresponding to the region of “La Vega” dam.

Figure 3(c) shows the detailed RSS map obtained applying the DPS method for the adopted ordered weight vector. The DPS method employs all three GBI bands; therefore, using the statistical pixel-based information the RSS map obtained shows a high-accurate classification without unclassified zones.

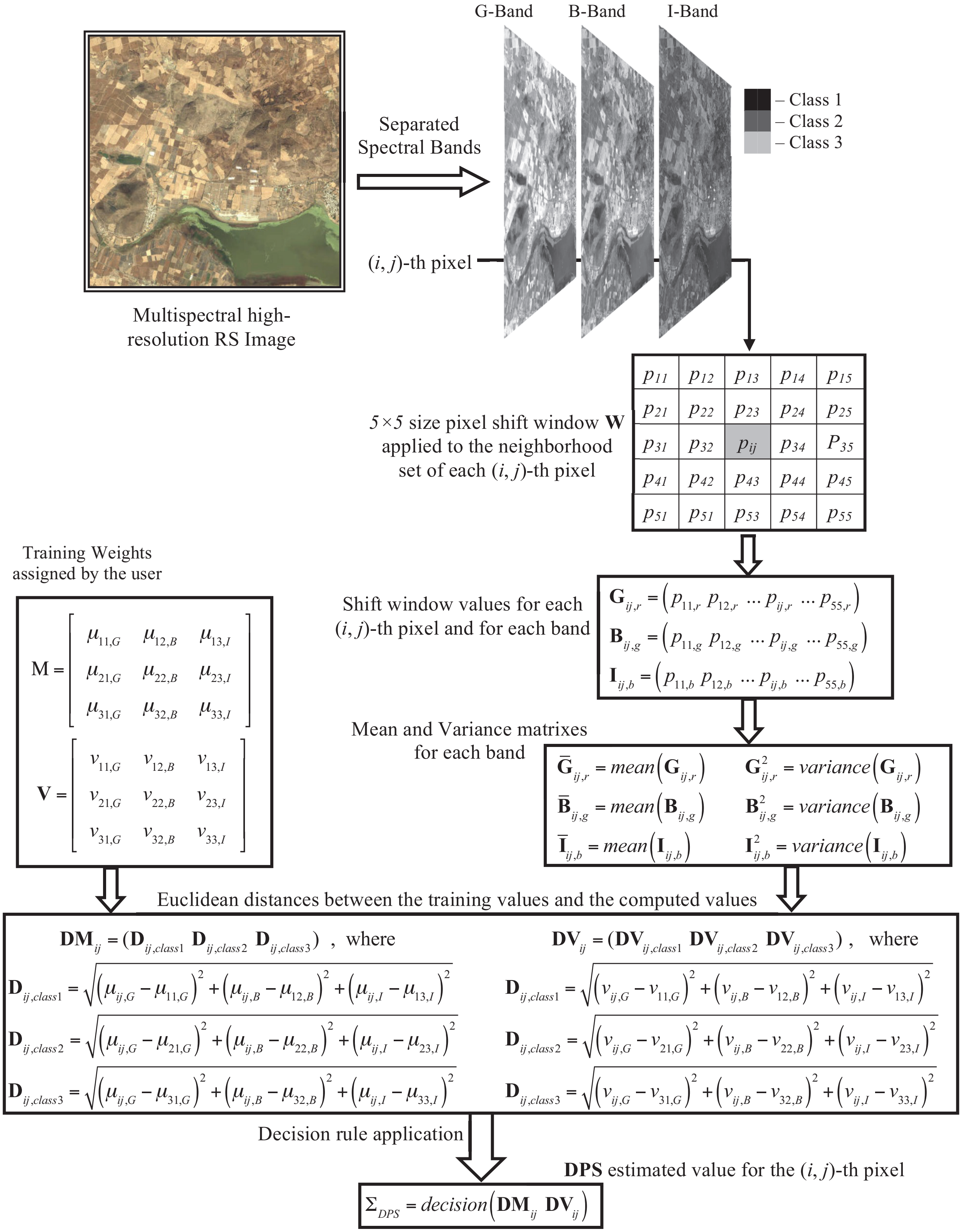
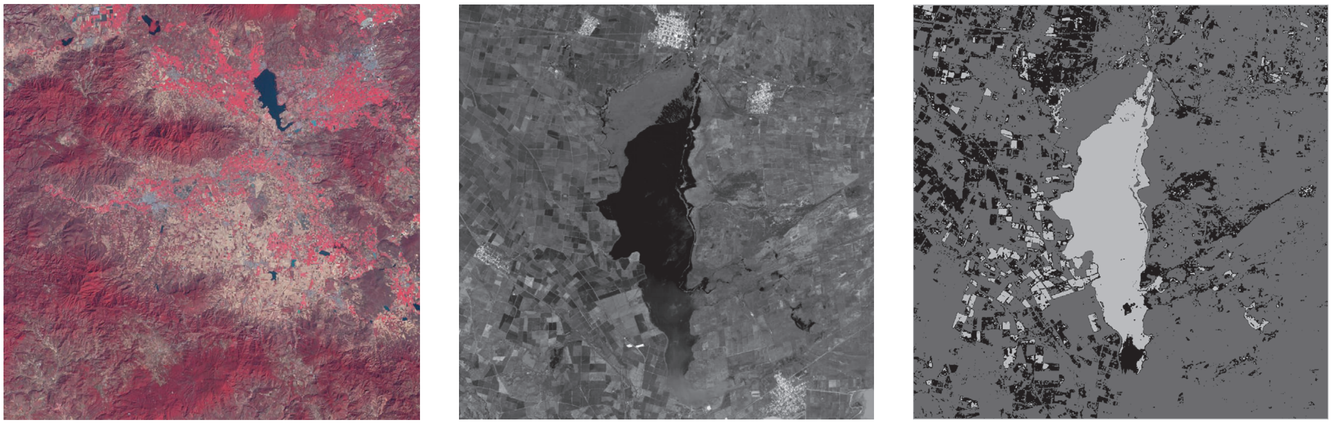


Figure 1. Processing structure of the DPS method.



(a) MRS image (courtesy of ERMEXS). (b) Detail of the MRS image (“La Vega” dam). (c) DPS classification detail of the MRS image.

Figure 3. MRS image classification using the DPS method.

7. CONCLUDING REMARKS

From the simulation results one may deduce that the developed DPS classifier provides a high-accurate classification without unclassified zones because it uses more robust information in the process (more than one spectral band). The values of both spectral and spatial resolutions of the MRS image are used to improve the performance of the algorithm, nevertheless and due to the quantity of information to use the computational complexity is high, therefore, distributed processing allows to reduce it. The processing time employed to obtain the RSS map was reduced to a 25% of the time needed for a traditional processing (without distributed computing methods).

The reported here simulation results shows the qualitative analysis of the overall performance of the DPS method, the quantitative analysis is a matter of further studies.

8. ACKNOWLEDGMENT

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