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CLASSIFICATION ALGORITHM FOR EMBEDDED SYSTEMS USING HIGH-RESOLUTION MULTISPECTRAL DATA

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ABSTRACT

The extraction of remote sensing signatures from a particular geographical region allows the generation of electronic signature maps, which are the basis to create a high-resolution collection atlas processed in discrete time. This can be achieved using an image classification approach based on pixel statistics for the class description, referred to as the multispectral pixel neighborhood method. This paper explores the effectiveness of this approach developed for supervised segmentation and classification of high-resolution remote sensing imagery using SPOT-5 data. Moreover, an analysis of the proposition for implementation as an embedded system is provided, to improve the processing time and reducing computational load, using a scheme based on hardware/software codesign techniques. Simulations are reported to probe the efficiency of the proposed technique.

Index Terms — Image Classification, Remote Sensing, Multispectral Data, Embedded Systems

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, those subjects are a mature and well developed research field, presented and detailed in many works ([1] thru [5] 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), and the computational processing time needed to classify those characteristics.

The development of a novel tool based on supervised segmentation and classification of remote sensing signatures (RSS) from multispectral remote sensing (MRS) imagery is based on the analysis of pixel statistics, and is referred to as the multispectral pixel neighborhood (MPN) 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 follow (the values are approximated, exact values depends on the particular MRS instruments [5]):

- 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 [6].

The image used for this research was provided by SPOT-5 through its Mexican office SIAP (from its Spanish acronym “Servicio de Información Agroalimentaria y Pesquera”) under the ERMEX-NG program (from its Spanish acronym “Estación de Recepción México Nueva Generación”) [7].

The spatial resolution of the image is 10m (spectral mode Hi) for a $6,000 \times 6,000$ 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. MULTISPECTRAL PIXEL NEIGHBORHOOD

The MPN method is based in statistical information of the pixel neighborhood for each spectral band, its classification rule is computationally simple. An extensive study was performed in [8] to probe that the accuracy obtained with this classification process is more efficient (both qualitatively and quantitatively) compared with other more computationally intensive algorithm. This algorithm is characterized by the mean and variance values of the defined signatures to be classified (set as classes), and the Euclidean distances based on the Pythagorean theorem to create the decision rule for classification.

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 5×5 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 MPN 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 MPN classifier.

5. HARDWARE/SOFTWARE CODESIGN

The hardware/software codesign (HSC) intends to concur the design of hardware and software components of complex electronic systems in order to optimize the performance of the processing task. It emerged as a new discipline to design complex integrated circuits in the early 1990s. Presently, its techniques are more used by companies that are developing embedded electronic systems and the application field is growing.

In a general view, the HSC started to be considered as the process of concurrent and coordinated design of an electronic system comprising hardware as well as software components based on a system description that is implemented by the aid of design automation [9]. In other

words, software techniques are used for features and flexibility, while hardware design is used for performance. Some of the current design methodologies are needed to specify the requirements for software and hardware separately. A specification is generally incomplete at the moment that is sent to the designers; therefore, the hardware/software partition is decided *a-priori* which leads to difficulties in verifying the entire system, and hence to incompatibilities across the boundary between both hardware and software.

The aim is to implement the MPN method for multispectral remote sensing classification as an embedded HSC system, to improve the processing time and reducing computational load.

6. VERIFICATION PROTOCOLS

To analyze the qualitative performance of the MPN technique, a multispectral test image is used. Figure 2 show the test image, containing three different regions (in yellow, blue and black colors) with a different pattern. Figure 3 shows the MPN classification result. The MPN method was implemented only as software.

7. SIMULATION EXPERIMENT

In the simulation results, a MRS image is used for RSS classification using the MPN 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 4 shows the original MPN high-resolution (spatial resolution of 10m, $6,000 \times 6,000$ pixels, approximately 60×60 kilometers) and multispectral image (three GBI spectral bands) in TIFF format, corresponding to the “Los Valles” region of the State of Jalisco in Mexico focused on a dam called “La Vega” [7]. Figure 5 shows the RSS map obtained applying the MRS method for the adopted ordered weight vector. The proposed method employs all three GBI bands; therefore, using the statistical pixel-based, neighborhood-based and band-based information the RSS map obtained shows a high accuracy on its classification.

As the test image, the MPN method was implemented only as software to probe its performance and accuracy. The design of the embedded HSC system to improve the processing time and reduce the computational load required is a matter of further studies.

8. CONCLUDING REMARKS

From the simulation results one may deduce that the MPN classifier provides an accurate classification without unclassified zones because it uses more robust information in the process.

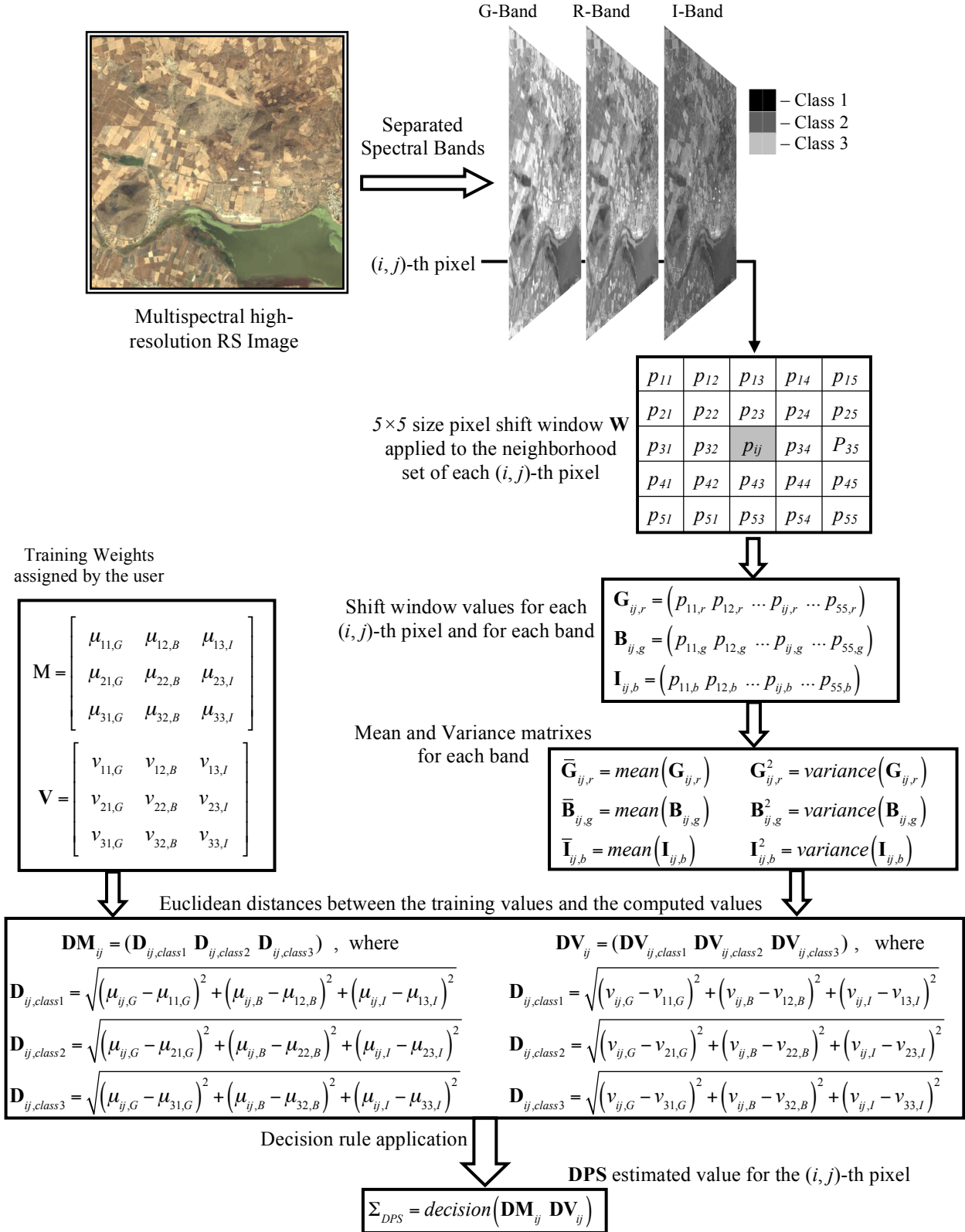


Figure 1. Processing structure of the MPN method.



Figure 2. Original Test image.



Figure 3. MPN classification for 3 classes.



Figure 4. MRS image (courtesy of ERMEX-NG).

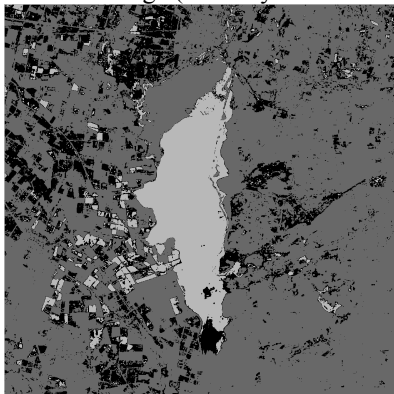


Figure 5. MPN classification of the MRS image.

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 used the computational complexity increase, therefore the design of an embedded HSC system to improve the processing time is required.

The reported results show the qualitative and software-based analysis of the overall performance of the MPN method. The design of the embedded HSC system is a matter of further studies.

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10. REFERENCES

- [1] S.W. Perry, H.S. Wong, and L. Guan, *Adaptive Image Processing: A Computational Intelligence Perspective*, CRC Press, U.S.A., 2002.
- [2] P.M. Mather, *Computer Processing of Remotely-Sensed Images*, John Wiley & Sons, U.S.A., 2004.
- [3] Y. Shkvarko, and I. Villalon-Turrubiates, “Remote sensing imagery and signature fields reconstruction via aggregation of robust regularization with neural computing”, in *Advanced Concepts for Intelligent Vision Systems*, J. Blanc-Talon, W. Philips, D. Popescu and P. Scheunders, Springer-Verlag, Germany, pp. 865-876, 2007.
- [4] J. R. Jensen, *Introductory Digital Image Processing: A Remote Sensing Perspective*, Prentice-Hall, U.S.A., 2005.
- [5] T. M. Lilliesand and R. K. Kiefer, *Remote Sensing and Image Interpretation*, John Wiley & Sons, U.S.A., 2008.
- [6] Satellite Imagery and Smart Mapping Solutions, <http://www.spotimage.com>, 2013.
- [7] Estación de Recepción México Nueva Generación – Servicio de Información Agroalimentaria y Pesquera, <http://www.siap.gob.mx>, 2013.
- [8] I.E. Villalon-Turrubiates, “Weighted Pixel Statistics for Multispectral Image Classification of Remote Sensing Signatures: Performance Study”, *Proceedings of the 5th IEEE International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE)*, Mexico City, pp. 534-539, 2008.
- [9] J. Teich, “Hardware/Software Codesign: The Past, The Present, and Predicting the Future”, *Proceedings of the IEEE*, vol. 100, pp. 1411-1430, 2012.