2016-07

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Ivan E. Villalon-Turrubiates, "Performance Evaluation of a Multispectral Classificator that Employs High-Performance Computing Techniques", en Proceedings of the 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS): Advancing the Understanding of Our Living Planet, Beijing China, 2016, pp. 3838-3841.

PERFORMANCE EVALUATION OF A MULTISPECTRAL CLASSIFICATOR THAT EMPLOYS HIGH-PERFORMANCE COMPUTING TECHNIQUES

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ABSTRACT

The classification procedure to identify remote sensing signatures from a particular geographical region can be achieved using an accurate image classification approach which is based on multispectral sets and uses pixel statistics for the class description, and it is referred to as the Multispectral Pixel Classification method. This paper presents a study of the performance that this approach provides for supervised segmentation and classification of sensed signatures for land use analysis and using high-performance computing techniques compared with traditional programming methodologies. The results obtained with this study uses real multispectral scenes obtained with remote sensing techniques (high-resolution optical images) to probe the efficiency of the classification technique.

Index Terms— image classification, remote sensing, image processing, multispectral.

1. INTRODUCTION

Considerable progress has been made in the application of remote sensing techniques to both research and operational solutions for urban planning and natural resource management. Modern applied theory of image processing is now a mature and well developed research field, presented and detailed in many works ([1] thru [6] 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). Moreover, there is an important necessity for a model that could be implemented with a high-performance computing technique to reduce the processing time until a suitable value that could be considered as real time. Is important to clarify that the concept of real time is completely related to the time in which the processing of the information is needed to be available.

The development of a novel tool for supervised segmentation and classification of remote sensing signatures (RSS) from multispectral remote sensing (MRS) imagery in real time is based on the analysis of pixel statistics, and is referred to as the multispectral pixel classification (MPC) method.

2. WEIGHTED ORDER STATISTICS METHOD

The weighted order statistics (WOS) method has been long used for classification in remotely sensed images [1]. It basically is considered as a generalization of the median filter, and is characterized by a weight vector and a threshold value. The order statistics (OS) filtering methodology [2] shifts a $n\times n$ window $\mathbf{W}$ (with cardinality $n\times n$, i.e., $|\mathbf{W}| = n\times n$) over an input remote sensing (RS) image (using only one spectral band) frame and, at each position of the frame, takes the $n\times n$ inputs ($w_{11}, w_{12},\ldots, w_{ij}, \ldots, w_{nn}$) under $\mathbf{W}_{ij}$ and then outputs the r-th element of the sorted input.

The WOS method is a generalization of the OS filter that is characterized by a weight vector $\mathbf{Y}_{ij} = (\upsilon_1, \upsilon_2, \ldots, \upsilon_{n\times n})$ of $n\times n$ positive weight thresholds w, $0 \leq w \leq 255$ (gray-level threshold). To compute the output of the filter, each input w is duplicated to the number of corresponding weight υ, then they are sorted and the w-th order element (median) is chosen as the output. This is expressed as

$$\mathbf{WOS}_{ij} = median(\mathbf{Y}_{ij}) \ , \qquad (1)$$

where $\mathbf{WOS}_{ij}$ is the weighted order of the (i, j)-th pixel of the image. The decision rule for classification based on the WOS filter determines that, based on the a priori information for class segmentation (number of classes to be classified and their respective thresholds), the WOS value for each image pixel is compared with the a priori thresholds (gray-level) and classified according to the most proximal value [4].

3. MULTISPECTRAL PIXEL CLASSIFICATION

Multispectral imaging is a technology originally developed for space-based imaging. Multispectral images are the main type of images acquired by RS radiometers. Usually, RS systems have from 3 to 7 radiometers; each one acquires one digital image (also called scene) in a small band of visible spectra, ranging around 450 nm to 690 nm (for the most common images obtained with digital cameras).

For different purposes, combinations of spectral bands can be used. They are usually represented with red (R), green (G) and blue (B) channels. This is referred to as true-color RS imagery [5].

The wavelengths for the spectral bands used for true-color RS images are as follows (the values are approximated; exact values depend on the particular RS instruments [6]):

1) *blue*: 450-520 nm,
2) *green*: 520-600 nm,
3) *red:* 600-690 nm.

The MPC classificatory rule is computationally simple and this study shows that it can result in classification accuracy comparable to other more computationally intensive algorithms (e.g. the WOS method described on the previous section). It is characterized by the mean and variance values of the RSS signatures (classes) and the Euclidean distances based on the Pythagorean Theorem.

The training data for class segmentation requires the number of RSS to be classified (c); the means matrix **M** ($c \times c$ size) that contains the mean values μ_{cc}: ($0 \leq \mu_{cc} \leq 255$, gray-level) of the RSS classes for each of the spectral bands within the image; and the variances matrix **V** ($c \times c$ size) that contains the variances of the RSS classes for each band. The matrix **M** and **V** represents the weights of the classification process.

Next, the image is separated in all the different spectral bands and each (i, j)-*th* pixel is statistically analyzed calculating the means and variances from a neighborhood set of *5x5* pixels for each spectral 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.

The decision rule used by the MPC method is based on the minimum distances gained between the weighted training data and the pixel statistics.

The MPC techniques provide a high level of RSS segmentation and classification.

The detailed stages of the computational algorithm of the MPC method for RSS classification of the MRS scenes is described as follows

1) Set the number of RSS to classify.
2) Select one point on the MRS image for each class to be classified.
3) Separate the spectral bands from the true-color MRS image.
4) The selected points determine the training weights that consist of the means matrix **M** and the variances matrix **V**. These matrixes contain the mean and variance of each point in the spectral bands, respectively.
5) For each (i, j)-th pixel in the spectral bands, respectively, perform the following process:
   - Set a *5x5* pixel neighbourhood shift window **W**.
   - Determine the mean of the shift window **W**.
   - Determine the variance of the shift window **W**.
   - Calculate the Euclidean distances between the means and the training means for each band and for each class.
   - Calculate the Euclidean distances between the variance and the training variances for each band and for each class.
   - Select the minimum class distance for the means.
   - Select the minimum class distance for the variances.
   - Perform a comparison between the class distance for the mean and the class distance for the variance, and classify the pixel according to the minimum value and the class from which is obtained.

4. VERIFICATION PROTOCOLS

A synthesized image is used, which have a size of *1024x1024*-pixels, it is a RGB image in TIFF format. The aim is to analyze the overall performance of the MPC technique and, moreover, a comparison with the results obtained with the classical WOS method. The synthesized image contains three different regions (in yellow, blue and black colors) with a different pattern; therefore, the WOS and MPC methods will classify three classes.

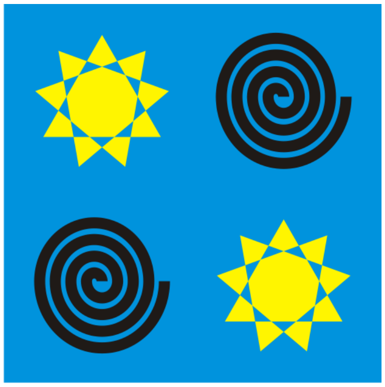
Figure 1(a) shows the synthesized test RGB scene. To perform the qualitative study, Figures 1(b) shows the results obtained with the WOS method. Figure 1(c) shows the results obtained with the developed MPC method. Both, the WOS and MPC methods performs a good qualitative classification, nevertheless, Figure 1(d), (e) and (f) shows some qualitative details from the classified synthesized image that probes the performance differences between the techniques.

The quantitative study is performed calculating the classified percentage obtained with the WOS and MPC methods, respectively, and compared with the original class quantities from the original synthesized scene. Table 1 shows the quantitative results.

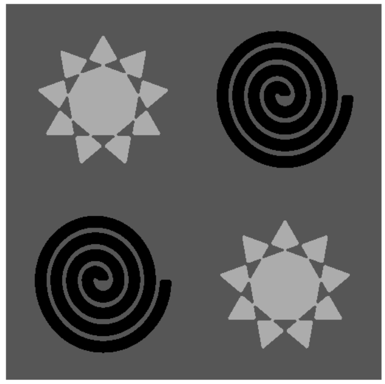
The theory of the WOS method defines that the classification is performed only using one spectral band [1]. The MPC method uses all the spectral bands within the image to analyze the pixel-level means and variances to perform a more accurate segmentation and classification.

From the qualitative details shown in Figure 1(d), (e) and (f), the MPC method performs a more accurate and less smoothed identification of the classes.

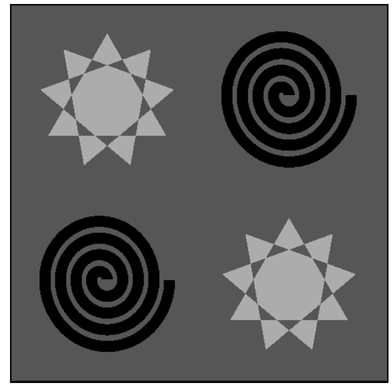
From the analysis of the quantitative results from Table 1, the MPC classified image provides a lower percentage points difference from the original synthesized image than the WOS classified image. Moreover, the WOS provide some unclassified zones due to its decision rule application [4]; the MPC method classifies all the pixels due to the use of pixel-based statistical training data. These qualitative and quantitative results probe the overall performance of the developed MPC technique.



(A) – SYNTHESIZED RGB IMAGE.



(B) – WOS CLASSIFICATION OF THE SYNTHESIZED RGB IMAGE FOR THREE CLASSES.



(C) – MPC CLASSIFICATION OF THE SYNTHESIZED RGB IMAGE FOR THREE CLASSES.

(D) – DETAIL OF THE SYNTHESIZED RGB IMAGE.

(E) – DETAIL OF THE OBTAINED WOS CLASSIFICATION FOR THE RGB IMAGE.

(F) – DETAIL OF THE OBTAINED MPC CLASSIFICATION FOR THE RGB IMAGE.

FIG. 1. SIMULATION RESULTS FOR THE SYNTHESIZED RGB IMAGES.

TABLE 1. COMPARATIVE TABLE OF THE CLASS PERCENTAGES OBTAINED BY THE CLASSIFICATION METHODS – SYNTHESIZED IMAGE

Method →		WOS method		MPC method	
	Original Image	%	Difference	%	Difference
Class 1	14.17	14.94	-0.77	15.82	-1.65
Class 2	73.90	72.47	+1.43	72.82	+1.08
Class 3	11.93	10.83	+1.10	11.36	+0.57
Unclass.		1.75	+1.75	0.00	+0.00
Percentage Points Difference →			5.05%		3.30%

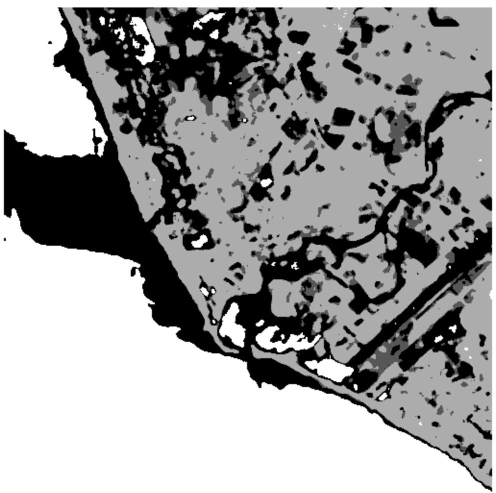
5. SIMULATION EXPERIMENT

As a simulation experiment, a real RSS electronic map is extracted from the MRS high-resolution image using the WOS and MPC methods. Figure 2(a) shows the MRS high-resolution *1024x1024*-pixels image in TIFF format with three spectral bands corresponding to the Banderas Bay in the city of Puerto Vallarta in Mexico [7]. Three level RSS are selected for this particular simulation process, moreover, unclassified zones must be also considered (2-bit classification) as:

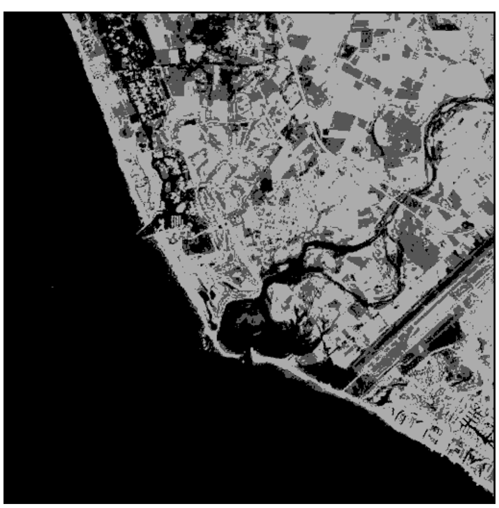
– RSS relative to the wet zones of the MRS image.
– RSS relative to the humid zones of the MRS image.
– RSS relative to the dry zones of the MRS image.
– Unclassified zones of the RSS map.

Figure 2(b) shows the RSS map obtained applying the WOS method for the adopted ordered weight vector. Figure 2(c) shows the RSS maps obtained applying the MPC method. The WOS method employs only one band to perform the classification [1], for this simulation the G band was used. The resulting RSS map shows a large unclassified zone.

(A) – ORIGINAL MRS IMAGE.



(B) – RSS MAP EXTRACTED WITH WOS.



(C) – RSS MAP EXTRACTED WITH MPC.

FIG. 2. SIMULATION RESULTS FOR RSS MAPS EXTRACTION FROM MRS IMAGERY.

This is due to the color gradient present on the original MRS image and the lack of supervised data [4]. The MPC method employs all the available bands within the MRS image; therefore, using the statistical pixel-based information the RSS map obtained shows a high-accurate classification without unclassified zones.

6. CONCLUDING REMARKS

From the simulation results one may deduce that the WOS classifier generates several unclassified zones; while the developed MPC classifier provides a high-accurate classification without unclassified zones because it uses more robust information in the processing (several spectral bands). The simplicity of the developed methodology allows a real time implementation as a high-performance computing technique. The reported results shows the qualitative analysis of the overall performance of the MPC method.

ACKNOWLEDGMENT

The author would like to thank the **Instituto Tecnológico y de Estudios Superiores de Occidente (ITESO)** of Mexico for the resources provided for this research under the project titled "*Desarrollo de modelos adaptivos para el procesamiento digital de señales multiespectrales de percepción remota y su implementación como software de alto desempeño*".

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