Remote Sensing Signatures Extraction for Hydrological Resources Management Applications

Villalón-Turrubiates, Iván E.

Iván E. Villalón-Turrubiates, "Remote Sensing Signatures Extraction for Hydrological Resources Management Applications", en Proceedings of the ACS/IEEE International Conference on Computer Systems and Applications (AICCSA), Rabat Marruecos, 2009, pp. 567-570.

REMOTE SENSING SIGNATURES EXTRACTION FOR HYDROLOGICAL RESOURCES MANAGEMENT APPLICATIONS

Ivan E. Villalon-Turrubiates, *Member*, *IEEE*
Department of Computer Sciences and Engineering – University of Guadalajara Campus Los Valles
Guadalajara-Ameca Highway Km. 45.5, 46600 Ameca Mexico,
Telephone: (+52) 3757580148 ext. 7267, E-mail: villalon@ieee.org

Abstract **–** The extraction of hydrological characteristics from a particular geographical region through remote sensing (RS) data processing allows the generation of electronic signature maps, which are the basis to create a high-resolution collection atlas processed in time for a particular geographical zone. This can be achieved using a novel tool developed for supervised segmentation and classification of hydrological remote sensing signatures (HRSS) via the combination of both statistical strategies defined as the Weighted Order Statistics (WOS) and the Minimum Distance to Means (MDM) techniques, unifying their particular advantages. This is referred to as the Hydrological Signatures Classification (HSC) method. The extraction of HRSS from real-world high-resolution environmental RS imagery is reported to probe the efficiency of the developed technique in hydrological resources management applications.

Keywords **–** Image processing, signal processing, remote sensing, image classification, geographical information.

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 hydrological 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 and descriptive regularization 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 those unsolved problems is particularly related to the extraction of hydrological characteristics (e.g., water, humid and dry content) for applications in resource management (modeling and planning). The development of a novel tool for the supervised segmentation and classification of the hydrological remote sensing signatures (HRSS) from remote sensing (RS) imagery unifies the statistical strategies based on weighted order statistics (WOS) and minimum distance to means (MDM) applications. This is addressed as the Hydrological Signatures Classification (HSC) method.

2. WEIGHTED ORDER STATISTICS

The WOS method is considered as a generalization of the median filter [1], 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 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, $0 \le w \le 255$ (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

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

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 HRSS 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.

3. MINIMUM DISTANCE TO MEANS

The MDM decision rule is computationally simple and can result in classification accuracy comparable to other more computationally intensive algorithms [3]. It is characterized by the mean values of the HRSS classes and the Euclidean distances based on the Pythagorean Theorem. An important aspect of this method is that it is applied to the multiband RS imagery. The a priori information for class segmentation (number of HRSS to be classified and their respective mean values) conform the means matrix **E** ($c \times b$ size) that contains the mean values μ_{cb}: ($0 \leq \mu_{cb} \leq 255$, gray-level) of the HRSS classes for every RS band. Here, c is the number of HRSS classes to be classified, and b is the number of spectral bands contained in the RS imagery. The input is defined by the vector $\mathbf{\Pi}_{ij}$, which contains the (i, j)-th image pixel values π_{ijb} employed for every spectral band. To compute the output of the classifier, the distance between each input $\mathbf{\Pi}_{ij}$ and the means matrix **E** is calculated using the Euclidean distance based on the Pythagorean Theorem. This is expressed by Eq. 2, where $\mathbf{D}_{ij,c}$ is a vector ordered by multi-index (ij,c) of $c \times 1$ size that contains the distances between the (i, j)-th image pixel value and the c-class value for each band b. The decision rule for classification based on the MDM filter determines that, based on the a priori information for class segmentation (number of HRSS to classify and their respective mean values), each image pixel generates an ordered distance vector $\mathbf{D}_{ij}$, and therefore, the pixel is classified according to the minimum value on the vector.

4. HYDROLOGICAL SIGNATURES CLASSIFICATION METHOD

Both WOS and MDM techniques provide a high level of HRSS segmentation and classification. Nevertheless, to ensure an accurate high-resolution process, the fusion of both algorithms is performed as a systematical tool for supervised HRSS segmentation and classification of RS scenes via combining the WOS and MDM techniques.

The developed technique is referred to as the Hydrological Signatures Classification (HSC) method [4]. The detailed stages of the computational algorithm of the HSC method for HRSS classification of the RS scenes is described as follows

1. Set the number of HRSS classes and their respective threshold mean values for each band in the multiband RS image. This is the a priori information.
2. Separate the multiband RS image in its respective bands (b).
3. Apply the WOS method (1) to each band b present on the RS image. With this, a number b of WOS classified HRSS images are obtained.
4. Apply the MDM method (2) using the WOS classified HRSS images as the bands b.
5. The classification obtained with the MDM method is the desired HSC electronic HRSS map extracted from the RS image.

5. HRSS SIMULATION EXPERIMENT

In the reported here simulation results, a HRSS electronic map is extracted from the RS high-resolution image. Both, the WOS and MDM methodologies employs a decision rule used for the classification process, nevertheless, some pixels from the original RS scene may have particular characteristics that causes a uncertainty in the decision rule (e.g., for the WOS method, the median of the weighted vector for a particular pixel is exactly between the values of two classes; for the MDM method, the distance to two or more classes are the same). In this case, the decision rule considers those pixels as unclassified zones.

Three level HRSS are selected for this particular simulation process, moreover, unclassified zones must be also considered (2-bit classification) described as

– Black regions represents the HRSS that relate to the wet zones of the RS image.

– Heavy-gray regions represents the HRSS that relate to the humid zones of the RS image.

– Light-gray regions represents the HRSS that relate to the dry zones of the RS image.

– White regions represent the unclassified zones of the HRSS map.

$$\mathbf{D}_{ij,c} = \sqrt{\left(\pi_{ij,1} - \mu_{c1}\right)^2 + \left(\pi_{ij,2} - \mu_{c2}\right)^2 + \ldots + \left(\pi_{ij,b} - \mu_{cb}\right)^2}, \qquad (2)$$

Table 1. Comparative table of the HRSS percentages produced by the classification methods.

Method →	Simplest	WOS method		MDM method		HSC method	
	Base [%]	%	Diff. with Base	%	Diff. with Base	%	Diff. with Base
Wet	46.84	34.90	-11.94	49.99	+3.15	46.94	+0.10
Humid	23.25	31.21	+7.96	23.91	+0.66	23.78	+0.53
Dry	29.91	16.06	-13.85	24.69	-5.22	27.41	-2.50
Unclass.	0.00	17.83	+17.83	1.41	+1.41	1.87	+1.87
Percentage Points Difference →			51.58%		10.44%		**5.00%**

Figure 1 show the original high-resolution (1024x1024-pixel) RS scene borrowed from the real-world [5] corresponding to a dam in the south of the Metropolitan area of Guadalajara city in Mexico. Figure 2 show the HRSS maps obtained applying the WOS method for the adopted ordered weight vector.

Figure 3 show the HRSS maps obtained applying the MDM method. Figure 4 show the HRSS maps obtained applying the fusion of the WOS and MDM approaches via the developed HSC method.

The simplest classification technique is based only in direct comparison of each pixel value of the RS image with the a priori information (mean value for each HRSS to be segmented) provided by the user [4]. This methodology provides a possibility to perform an accurate HRSS extraction; nevertheless, the interaction with the user to perform the final verification is needed, therefore this approach is used for comparison purposes only.

Taking this into account, quantitative measurements are performed based on the simplest supervised classification results. Table 1 reports the HRSS contents in percentage for the WOS, MDM and HSC methods, respectively, and their perceptual differences with the base method (simplest classification technique).

6. CONCLUDING REMARKS

From the simulation results one may deduce that the WOS classifier generates several unclassified zones; while the MDM classifier is more accurate because it uses more robust information in the processing (several image spectral bands), nevertheless, despite the fact that few zones are unclassified the results have a considerable density of unclassified unity-pixels.

The developed HSC method that fuses the WOS and MDM classifiers provides the high resolution HRSS electronic map with a high-accurate classification and less unclassified zones than those WOS and MDM without fusion. This is achieved because the unified HSC classifier uses more detailed robust a priori information from the original RS scene (provided by separate supervised classifiers). The resulting HRSS map ensures better results in the classification achieved with the developed HSC method. This is probed by the HRSS percentages obtained with the proposed HSC method, which manifest the lowest percentage difference to those ideally obtained with the simplest supervised classification technique.

The developed HSC method for HRSS extraction can be applied to several RS images from a particular geographical region obtained in different moments of time to generate a HRSS atlas of environmental electronic maps. This process is a powerful tool for hydrological resource management applications [4].

7. ACKNOWLEDGEMENT

The author would like to thank the “Programa de Mejoramiento del Profesorado PROMEP” of the Public Education Secretary (SEP) of Mexico and the University of Guadalajara for the resources provided for this research under the research project number PROMEP/103.5/08/2919 and titled “Agregación de métodos para el mapeo y caracterización del medio ambiente mediante técnicas de percepción remota”.

Figure 1. Original high-resolution RS scene.

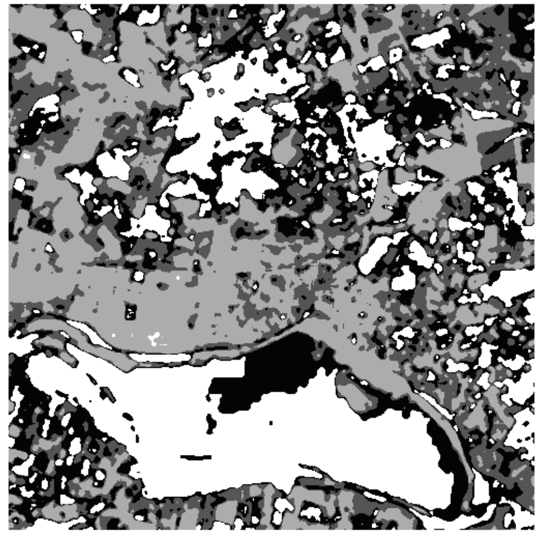

Figure 2. HRSS map extracted using the WOS method.

Figure 3. HRSS map extracted using the MDM method.

Figure 4. HRSS map extracted using the fused HSC method.

8. 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] R. Porter, D. Eads, D. Hush and J. Theiler, "Weighted Order Statistics Classifiers with Large Rank-Order Margin", *Proceedings of the 20th International Conference on Machine Learning*, Washington U.S.A., 2003.

[3] P.M. Mather, *Computer processing of remotely-sensed images*, John Wiley & Sons, U.S.A., 2004.

[4] 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, Ed. Germany: Springer-Verlag, pp. 865-876, August 2007.

[5] GeoEye – Innovative Geospatial Products and Solutions, http://www.geoeye.com, 2009.