

Instituto Tecnológico y de Estudios Superiores de Occidente

Repositorio Institucional del ITESO

rei.iteso.mx

Departamento de Electrónica, Sistemas e Informática

DESI - Artículos y ponencias con arbitraje

2014-07

Dynamical Characterization of Land-Use Classification using Multispectral Remote Sensing Data for Guadalajara Region

Villalón-Turrubiates, Iván E.

I.E. Villalón-Turrubiates (2014). "Dynamical Characterization of Land-Use Classification using Multispectral Remote Sensing Data for Guadalajara Region". Proceedings of the 2014 IEEE International Geoscience and Remote Sensing Symposium (IGARSS): Energy and our Changing Planet, Québec, Canadá, 2014, pp.145-148.

Enlace directo al documento: <http://hdl.handle.net/11117/3243>

Este documento obtenido del Repositorio Institucional del Instituto Tecnológico y de Estudios Superiores de Occidente se pone a disposición general bajo los términos y condiciones de la siguiente licencia:
<http://quijote.biblio.iteso.mx/licencias/CC-BY-NC-2.5-MX.pdf>

(El documento empieza en la siguiente página)

DYNAMICAL CHARACTERIZATION OF LAND USE CLASSIFICATION USING MULTISPECTRAL REMOTE SENSING DATA FOR GUADALAJARA REGION

Ivan E. Villalon-Turrubiates, *Senior Member, IEEE*

Instituto Tecnológico y de Estudios Superiores de Occidente (ITESO), Universidad Jesuita de Guadalajara
Periférico Sur Manuel Gómez Morín 8585, 45604 Tlaquepaque Jalisco México
Telephone: (+52 33) 3669-3434+3873, E-mail: villalon@ieee.org

ABSTRACT

An intelligent post-processing computational paradigm based on the use of dynamical filtering techniques modified to enhance the quality of reconstruction of remote sensing signatures based on SPOT-5 imagery is proposed. As a matter of particular study, a robust algorithm is reported for the analysis of the dynamic behavior of geophysical indexes extracted from remotely sensed scenes. Simulations are reported to probe the efficiency of the proposed technique.

Index Terms — Image Classification, Remote Sensing, Multispectral Data, Dynamical Analysis

1. INTRODUCTION

Intelligent post-processing of environmental data is now a mature and developed research field, presented and detailed in many works (see for example, recent studies [1] thru [9] and the references therein). Although the existing methods offer a manifold of efficient statistical and descriptive regularization techniques to tackle with the particular environmental monitoring problems, in many application areas there still remain some unresolved theoretical and data processing problems related particularly to the extraction and analysis of the dynamical behavior of geophysical characteristics for decision support applications. In particular, the crucial data processing aspect is how to incorporate a remote sensing signatures (RSS) extraction method with a robust dynamic analysis technique for evaluation and prediction of the behavior of the particular index monitored in environmental processes.

In this study, a robust filtering method is proposed and verified via computational simulations, which provides the possibility to track, filter and predict the dynamical behavior of the RSS using remote sensing (RS) scenes based on SPOT-5 imagery provided with the use of the Weighted Pixel Statistics (WPS) method [9]. The proposed methodology aggregates the WPS method with a dynamical filtering technique [3] via the Multispectral Dynamics Method (MDM). In the simulations, the process is tested with the use of SPOT-5 imagery [10].

This study intends to show the foundations in understanding the basic theoretical and computational aspects of how to aggregate the end-user-oriented intelligent

post-processing of RSS hydrological electronic maps with the dynamic filtering paradigm (via MDM) for intelligent analysis of the dynamical behavior of the remotely monitored scenes. The reported results of simulations and their analysis are indicative of a usefulness of the proposed approach for monitoring the geophysical characteristics, and those could be addressed for different end-user-oriented resources management applications.

2. PROBLEM MODEL

Consider the measurement data wavefield $u(\mathbf{y})=s(\mathbf{y})+n(\mathbf{y})$ modeled as a superposition of the echo signals s and additive noise n that assumed to be available for observations and recordings within the prescribed time-space observation domain $Y \ni \mathbf{y}$. The model of observation wavefield u is specified by the linear stochastic equation of observation (EO) of operator form [1] as $u=Se+n$ ($e \in E$; $u, n \in U$; $S: E \rightarrow U$) in the L_2 Hilbert signal spaces E and U [1] with the metric structures induced by inner products,

$$[e_1, e_2]_E = \int_{F \times X} e_1(f, \mathbf{x}) e_2^*(f, \mathbf{x}) df d\mathbf{x}, [u_1, u_2]_U = \int_Y u_1(\mathbf{y}) u_2^*(\mathbf{y}) d\mathbf{y}, \quad (1)$$

respectively, where $*$ stands for complex conjugate. The operator model of the stochastic EO in the conventional integral form may be rewritten as [1]

$$u(\mathbf{y}) = \int_{F \times X} S(\mathbf{y}, \mathbf{x}) e(f, \mathbf{x}) df d\mathbf{x} + n(\mathbf{y}), \quad (2)$$

$$e(f, \mathbf{x}) = \int_T \varepsilon(t, \mathbf{x}) \exp(-j2\pi ft) dt,$$

where $\varepsilon(t, \mathbf{x})$ represents the stochastic backscattered wavefield fluctuating in time t , and the functional kernel $S(\mathbf{y}, \mathbf{x})$ of the signal formation operator (SFO) S in (2) is specified by the particular employed RS signal wavefield formation model [2]. The phasor $e(f, \mathbf{x})$ in (2) represents the backscattered wavefield $e(f)$ over the frequency-space observation domain $F \times P \times \Theta$ [1], in the slant range $\mathbf{p} \in P$ and azimuth angle $\boldsymbol{\theta} \in \Theta$ domains, $\mathbf{x} = (\mathbf{p}, \boldsymbol{\theta})^T$, $\mathbf{X} = P \times \Theta$, respectively. The RS imaging problem is to find an estimate $\hat{B}(\mathbf{x})$ of the power spatial spectrum pattern (SSP) $B(\mathbf{x})$ ([3] and [4]) in the $X \ni \mathbf{x}$ environment via processing whatever values of measurements of the data wavefield $u(\mathbf{y})$, $\mathbf{y} \in Y$ are

available. Following the RS methodology [1], any particular RSS of interest is to be extracted from the reconstructed RS image $\hat{B}(\mathbf{x})$ applying the so-called signature extraction operator Λ [5]. The particular RSS is mapped applying Λ to the reconstructed image, i.e.

$$\hat{\Lambda}(\mathbf{x}) = \Lambda(\hat{B}(\mathbf{x})). \quad (3)$$

Taking into account the RSS extraction model (3), the signature reconstruction problem is formulated as follows: to map the reconstructed particular RSS of interest $\hat{\Lambda}(\mathbf{x}) = \Lambda(\hat{B}(\mathbf{x}))$ over the observation scene $X \ni \mathbf{x}$ via post-processing (4) whatever values of the reconstructed scene image $\hat{B}(\mathbf{x})$, $\mathbf{x} \in X$ are available.

3. IMAGE SEGMENTATION AND CLASSIFICATION

The development of a tool for supervised segmentation and classification of RSS from multispectral images is based on the analysis of pixel statistics, and is referred to as the weighted pixel statistics (WPS) method [9]. The WPS classificatory rule is computationally simple and provides classification accuracy comparable to other more computationally intensive algorithms [9]. It is characterized by the mean and standard deviation values of the RSS signatures (classes) and the Euclidean distances based on the Pythagorean theorem. An important aspect of this method is that it is applied to multispectral images.

The training data for class segmentation requires the number of RSS to be classified (c); the means matrix \mathbf{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 band; and the standard deviations matrix \mathbf{S} ($c \times c$ size) that contains the standard deviations of the RSS classes for each band. The matrix \mathbf{M} and \mathbf{S} represents the weights of the classification process. Next, the image is separated in the spectral bands and each (i, j) -th pixel is statistically analyzed calculating the means and standard deviations from a neighborhood set of 5×5 pixels for each 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 standard deviations, respectively.

The decision rule used by the WPS method is based on the minimum distances gained between the weighted training data and the pixel statistics. The WPS techniques provide a high level of RSS segmentation and classification. For this particular study, covered water, humid and dry zones are analyzed as land use classification.

4. DYNAMICAL MDM COMPUTING

4.1 RSS Lineal Dynamic Model

The crucial issue in application of the modern dynamic filter theory to the problem of reconstruction of the desired RSS in

time is related to modeling of the data as a random field (spatial map developing in time t) that satisfies a dynamical state equation. Following the typical linear assumptions for the development of the RSS in time [8] its dynamical model can be represented in a vectorized space-time form defined by a stochastic differential state equation of the first order

$$\frac{d\mathbf{z}(t)}{dt} = \mathbf{F}\mathbf{z}(t) + \mathbf{G}\xi(t), \quad \Lambda(t) = \mathbf{C}\mathbf{z}(t) \quad (4)$$

where $\mathbf{z}(t)$ is the so-called model state vector, \mathbf{C} defines a linear operator that introduces the relationship between the RSS and the state vector $\mathbf{z}(t)$, and $\xi(t)$ represents the white model generation noise vector characterized by the statistics $\langle \xi(t) \rangle = \mathbf{0}$ and $\langle \xi(t)\xi^T(t') \rangle = \mathbf{P}_\xi(t)\delta(t-t')$ [8]. Here, $\mathbf{P}_\xi(t)$ is referred to as state model disperse matrix [8] that characterizes the dynamics of the state variances developing in a continuous time t ($t_0 \rightarrow t$) starting from the initial instant t_0 .

The dynamic model equation that states the relationship between the time-dependent SSP (actual scene image) $\mathbf{B}(t)$ and the desired RSS map $\Lambda(t)$ represented as [8]

$$\hat{\mathbf{B}}(t) = \mathbf{H}(t)\mathbf{z}(t) + \mathbf{v}(t), \quad \mathbf{H}(t) = \mathbf{L}\mathbf{C}(t), \quad (5)$$

where \mathbf{L} is the linear approximation (i.e. first order matrix-form approximation [3]) to the inverse of the RSS operator $\Lambda(\hat{B}(\mathbf{r}))$. The stochastic differential model (4) and (5) allows the application of dynamical filter theory [3], [4] to reconstruct the desired RSS in time incorporating the a priori model of dynamical information about the RSS.

The aim of the dynamic filtration is to find an optimal estimate of the desired RSS $\hat{\Lambda}(t) = \mathbf{C}\hat{\mathbf{z}}(t)$ developing in time t ($t_0 \rightarrow t$) via processing the reconstructed image vector $\hat{\mathbf{B}}(t)$ and taking into considerations the a priori dynamic model of the desired RSS specified through the state equation (4). In other words, the design of an optimal dynamic filter that, when applied to the reconstructed image $\hat{\mathbf{B}}(t)$, provides the optimal estimation of the desired RSS map $\hat{\Lambda}(t)$, in which the state vector estimate $\hat{\mathbf{z}}(t)$ satisfies the a priori dynamic behavior modeled by the stochastic dynamic state equation (4). The canonical discrete time solution to (4) in state variables [9] is described as follows,

$$\mathbf{z}(i+1) = \Phi(i)\mathbf{z}(i) + \Gamma(i)\mathbf{x}(i), \quad \Lambda(i) = \mathbf{C}(i)\mathbf{z}(i), \quad (6)$$

where $\Phi(i) = \mathbf{F}(t_i)\Delta t + \mathbf{I}$, $\Gamma(i) = \mathbf{G}(t_i)\Delta t$, and Δt represents the time sampling interval for dynamical modeling of the RSS in discrete time. The statistical characteristics of the a priori information in discrete-time [8] are specified as

- 1) *Generating noise*: $\langle \xi(i) \rangle = \mathbf{0}$; $\langle \xi(i)\xi^T(j) \rangle = \mathbf{P}_\xi(i, j)$;
- 2) *Data noise*: $\langle \mathbf{v}(k) \rangle = \mathbf{0}$; $\langle \mathbf{v}(i)\mathbf{v}^T(j) \rangle = \mathbf{P}_v(i, j)$;
- 3) *State vector*: $\langle \mathbf{z}(0) \rangle = \mathbf{m}_z(0)$; $\langle \mathbf{z}(0)\mathbf{z}^T(0) \rangle = \mathbf{P}_z(0)$.

The $\mathbf{0}$ argument implies the initial state for initial time instant ($i=0$). For such model conventions, the disperse matrix $\mathbf{P}_z(0)$ satisfies the following disperse dynamic equation [8]

$$\mathbf{P}_z(i+1) = \mathbf{\Phi}(i)\mathbf{P}_z(i)\mathbf{\Phi}^T(i) + \mathbf{\Gamma}(i)\mathbf{P}_\xi(i)\mathbf{\Gamma}^T(i). \quad (7)$$

4.2 Dynamic RSS Reconstruction

The problem is to design an optimal decision procedure that, when applied to all reconstructed images $\{\hat{\mathbf{B}}(i)\}$ in discrete time i ($i_0 \rightarrow i$), provides an optimal solution to the desired RSS represented via the estimate of the state vector state vector $\mathbf{z}(i)$ subject to the numerical dynamic model (6). To proceed with the derivation of such a filter, the state equation (4) in discrete time i ($i_0 \rightarrow i$) is represented as

$$\mathbf{z}(i+1) = \mathbf{\Phi}(i)\mathbf{z}(i) + \mathbf{\Gamma}(i)\xi(i), \quad (8)$$

according to this dynamical model, the anticipated mean value for the state vector can be expressed as

$$\mathbf{m}_z(i+1) = \langle \mathbf{z}(i+1) \rangle = \langle \mathbf{z}(i+1) | \hat{\mathbf{z}}(i) \rangle, \quad (9)$$

where the $\mathbf{m}_z(i+1)$ is considered as the a priori conditional mean-value of the state vector for the $(i+1)$ estimation step

$$\mathbf{m}_z(i+1) = \mathbf{\Phi} \langle \mathbf{z}(i) | \hat{\mathbf{B}}(0), \hat{\mathbf{B}}(1), \dots, \hat{\mathbf{B}}(i) \rangle + \mathbf{\Gamma} \langle \xi(i) \rangle = \mathbf{\Phi} \hat{\mathbf{z}}(i) \quad (10)$$

and the prognosis of the mean-value becomes $\mathbf{m}_z(i+1) = \mathbf{\Phi} \hat{\mathbf{z}}(i)$. From (8) thru (10) is possible to deduce that given the fact that the particular reconstructed image $\hat{\mathbf{B}}(i)$ is treated at discrete time i , it makes the previous reconstructions $\{\hat{\mathbf{B}}(0), \hat{\mathbf{B}}(1), \dots, \hat{\mathbf{B}}(i-1)\}$ irrelevant; hence the optimal filtering strategy is reduced to the dynamical one-step predictor. Thus, the dynamical estimation strategy is modified to one-step optimal prediction procedure

$$\hat{\mathbf{z}}(i+1) = \langle \mathbf{z}(i+1) | \hat{\mathbf{z}}(i), \hat{\mathbf{B}}(i+1) \rangle = \langle \mathbf{z}(i+1) | \hat{\mathbf{B}}(i+1); \mathbf{m}_z(i+1) \rangle \quad (11)$$

hence, for the evolution $(i+1)$ st discrete-time prediction-estimation step, the dynamical RSS estimate (5) becomes

$$\hat{\mathbf{B}}(i+1) = \mathbf{H}(i+1)\mathbf{z}(i+1) + \mathbf{v}(i+1) \quad (12)$$

with the a priori predicted mean (9) for the desired state vector. Applying the Wiener minimum risk strategy [8] to solve (12) with respect to the state vector $\mathbf{z}(i)$ and taking into account the a priori information, the dynamic solution for the RSS state vector becomes

$$\hat{\mathbf{z}}(i+1) = \mathbf{m}_z(i+1) + \mathbf{\Sigma}(i+1) [\hat{\mathbf{B}}(i+1) - \mathbf{H}(i+1)\mathbf{m}_z(i+1)] \quad (13)$$

where the desired dynamic filter operator $\mathbf{\Sigma}(i+1)$ is

$$\begin{aligned} \mathbf{\Sigma}(i+1) &= \mathbf{K}_\Sigma(i+1)\mathbf{H}^T(i+1)\mathbf{P}_v^{-1}(i+1), \\ \mathbf{K}_\Sigma(i+1) &= [\mathbf{\Psi}_\Sigma(i+1) + \mathbf{P}_z^{-1}(i+1)]^{-1}, \\ \mathbf{\Psi}_\Sigma(i+1) &= \mathbf{H}^T(i+1)\mathbf{P}_v^{-1}(i+1)\mathbf{H}(i+1). \end{aligned} \quad (14)$$

Using the derived filter equations (13) and (14) and the initial RSS state model given by (6), the optimal filtering procedure for dynamic reconstruction becomes

$$\hat{\mathbf{\Lambda}}(i+1) = \mathbf{\Phi}(i)\hat{\mathbf{z}}(i) + \mathbf{\Sigma}(i+1) [\hat{\mathbf{B}}(i+1) - \mathbf{H}(i+1)\mathbf{\Phi}(i)\hat{\mathbf{z}}(i)] \quad (15)$$

with the initial condition $\hat{\mathbf{\Lambda}}(0) = \mathbf{\Lambda}\{\hat{\mathbf{B}}(0)\}$. The crucial issue to note here is related to model uncertainties regarding the particular employed dynamical RSS model (6), hence the model mismatch uncertainties regarding the overall dynamically reconstructed RSS.

5. SIMULATIONS

In the simulation results, a hydrological RSS electronic map is extracted from a multispectral SPOT-5 image using the WPS methods. Three level of 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.
-  – RSS relative to the humid zones.
-  – RSS relative to the dry zones.
-  – Unclassified zones of the RSS map.

Figure 1 shows the 1024×1024 -pixels RGB image in TIFF format corresponding to the Metropolitan area of Guadalajara in Mexico.

Figure 2 shows the hydrological RSS map obtained applying the WPS method for the adopted ordered weight vector. The WPS method was designed for multispectral images; therefore, using the statistical pixel-based information the hydrological RSS map obtained shows a high-accurate classification without unclassified zones.

Figure 3 shows the results of the dynamical analysis obtained after the processing several hydrological RSS maps (images not shown) in discrete-time with the application of the derived MDM algorithm (15). These simulations present the evolution in time of the physical characteristics specified via the hydrological RSS maps. The black color represents the changing zones of the multispectral image.

6. CONCLUDING REMARKS

In this paper, the dynamical approach for solving the nonlinear inverse problems of high-resolution dynamical reconstruction of the hydrological RSS of the environmental scenes is presented via processing the finite-dimensional space-time measurements of the available sensor data. The dynamical RSS post-processing scheme reveals some possible approach toward a dynamic computational paradigm for numerical reconstruction and filtration of different RSS maps in discrete time. The presented study establishes the foundation to assist in understanding the basic theoretical and computational aspects of remote sensing image enhancement, extraction of physical scene characteristics and their dynamical post-processing. The reported results of simulation study are indicative of a usefulness of the proposed approach for monitoring the physical environmental characteristics, and those could be addressed for different end-user-oriented environmental resource management applications.



Figure 1. Original multispectral scene.

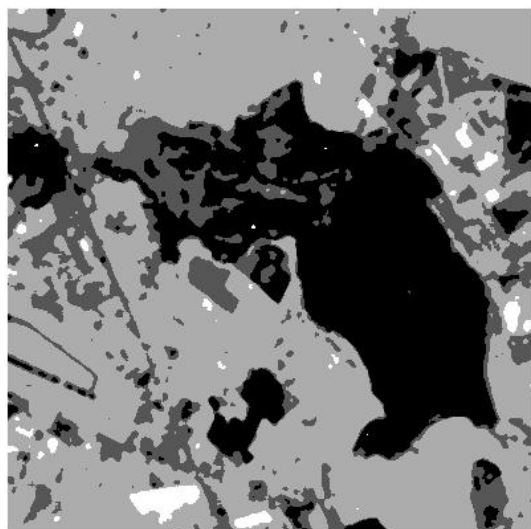


Figure 2. RSS hydrological map extracted with WPS.

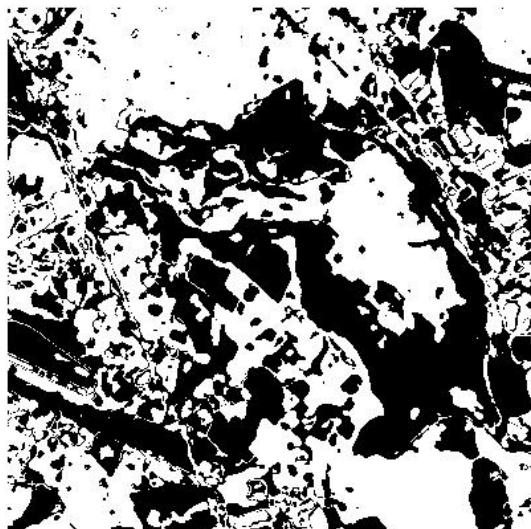


Figure 3. Dynamic RSS hydrological map obtained with MDM.

7. 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 multispectrales de percepción remota y su implementación como software de alto desempeño*”.

8. REFERENCES

- [1] Y.V. Shkvarko, “Estimation of wavefield power distribution in the remotely sensed environment: bayesian maximum entropy approach”, *IEEE Transactions on Signal Processing*, vol. 50, 2002, pp. 2333-2346.
- [2] B.R. Mahafza, *Radar Systems Analysis and Design Using MATLAB*, CRC Press, USA, 2000.
- [3] Y.V. Shkvarko and I.E. 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, P. Scheunders, Eds. Berlin: Springer-Verlag, 2007, pp. 235-246.
- [4] Y.V. Shkvarko and I.E. Villalon-Turrubiates, “Computational enhancement of large scale environmental imagery: aggregation of robust numerical regularization, neural computing and digital dynamic filtering”, in *Journal of Computational Science and Engineering*, vol. 3, Inderscience Eds. 2007, pp. 219-231.
- [5] Ivan E. Villalon-Turrubiates, “Dynamical Processing of Geophysical Signatures based on SPOT-5 Remote Sensing Imagery”, *Proceedings of the IEEE Int. Geoscience and Remote Sensing Symposium*, Hawaii, 2010, pp. 2244-2247.
- [6] S.W. Perry, S.W. H.S. Wong and L. Guan, *Adaptive Image Processing: A Computational Intelligence Perspective*, CRC Press, USA, 2002.
- [7] T. M. Lilliesand and R. K. Kiefer, *Remote Sensing and Image Interpretation*, John Wiley & Sons, U.S.A., 2008.
- [8] S.E. Falkovich, V.I. Ponomaryov and Y.V. Shkvarko, *Optimal Reception of Space-Time Signals in Channels with Scattering*, Radio I Sviaz, Russia, 1989.
- [9] 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.
- [10] Satellite Imagery and Smart Mapping Solutions, <http://www.spotimage.com>, 2014.