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A Dynamical Model To Classify The Content Of Multitemporal Images Employing Distributed Computing Techniques

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ABSTRACT

An intelligent post-processing paradigm based on the use of a dynamical filtering technique modified to enhance the reconstruction quality of remote sensing indexes using multitemporal images and distributed computing techniques is proposed. As a matter of particular study, a robust algorithm is reported for the analysis of the dynamic behavior of geophysical signatures extracted from remotely sensed scenes. The simulation results prove the efficiency of the proposed technique along with the computational implementation based on a big-data framework using distributed processing.

Index Terms – Remote Sensing, Multispectral Imaging, Geodynamics, Distributed Computing

1. INTRODUCTION

Intelligent post-processing of environmental data is now a mature and developed research field, presented and detailed in many works (for example [1] thru [7] 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, and its implementation using big-data techniques in order to improve the processing time and reduce the computational resources needed.

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 a particular monitored index.

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 multitemporal remote sensing (MRS) scenes based on SPOT-5 images [9].

The proposed methodology aggregates the Weighted Pixel Statistics (WPS) method [7] with a dynamical filtering technique [3] and a framework that allows distributed processing of large data sets across clusters of computers [8] via the Multitemporal Dynamic Analysis (MDA) model.

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:

$$[e_1,e_2]_{\mathrm{E}} = \int_{F\times X} e_1(f,\mathbf{x})e_2^*(f,\mathbf{x})dfd\mathbf{x}\ ,$$
$$[u_1,u_2]_{\mathrm{U}} = \int_{Y} u_1(\mathbf{y})u_2^*(\mathbf{y})d\mathbf{y}\ , \tag{1}$$

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

$$u(\mathbf{y}) = \int_{F\times X} S(\mathbf{y},\mathbf{x})e(f,\mathbf{x})dfd\mathbf{x} + n(\mathbf{y})\ ,$$
$$e(f,\mathbf{x}) = \int_{T} \varepsilon(t;\mathbf{x})\exp(-j2\pi ft)dt\ , \tag{2}$$

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 MRS 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 $\rho\in P$ and azimuth angle $\theta\in\Theta$ domains, $\mathbf{x}=(\rho,\theta)^{\mathrm{T}}$, $\mathbf{X}=P\times\Theta$, respectively.

The MRS imaging problem is to find an estimate $\hat{B}(\mathbf{x})$ of the power spatial spectrum pattern (SSP) $B(\mathbf{x})$ [3] 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 MRS methodology [1], any particular RSS of interest is to be extracted from the reconstructed MRS image $\hat{B}(\mathbf{x})$ applying the so-called signature extraction operator Λ [4].

The particular RSS is mapped applying Λ to the reconstructed image as

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

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 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 MRS scenes is based on the analysis of pixel statistics, and is referred to as the WPS method [7], where its classification rule is computationally simple and provides an optimal level of accuracy compared with other more common and computationally intensive algorithms [7] for real-time requirements. It is characterized by the mean and standard deviation values of the RSS signatures (classes) and the Euclidean distances based on the Pythagorean theorem. Moreover, the robustness of the WPS methodology increases with the use of multispectral images.

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 $\square_{cc}$: ($0 \le \square_{cc} \le 255$, gray-level) of the RSS classes for each band; and the standard deviations matrix **S** ($c \times c$ size) that contains the standard deviations of the RSS classes for each band. The matrix **M** and **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 *5x5* 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.

4. MULTITEMPORAL DYNAMIC ANALYSIS (MDA) FRAMEWORK

4.1 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 [6] its dynamical model can be represented in a vectorized space-time form defined by a stochastic differential state equation of the first order

$$\frac{d\mathbf{z}(t)}{dt} = \mathbf{Fz}(t) + \mathbf{G}\boldsymbol{\xi}(t) , \quad \boldsymbol{\Lambda}(t) = \mathbf{Cz}(t) \tag{4}$$

where $\mathbf{z}(t)$ is the so-called model state vector, **C** defines a linear operator that introduces the relationship between the RSS and the state vector $\mathbf{z}(t)$, and $\boldsymbol{\xi}(t)$ represents the white model generation noise vector characterized by the statistics $\langle \boldsymbol{\xi}(t) \rangle = \mathbf{0}$ and $\langle \boldsymbol{\xi}(t)\boldsymbol{\xi}^T(t') \rangle = \mathbf{P}_{\xi}(t)\delta(t-t')$ [6]. Here, $\mathbf{P}_{\xi}(t)$ is referred to as state model disperse matrix [6] that characterizes the dynamics of the state variances developing in a continuous time t ($t_0 \to t$) 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 $\boldsymbol{\Lambda}(t)$ represented as

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

where **L** is the linear approximation 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] 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 $\hat{\boldsymbol{\Lambda}}(t) = \mathbf{C}\hat{\mathbf{z}}(t)$ developing in time t ($t_0 \to t$) 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 $\hat{\boldsymbol{\Lambda}}(t)$, 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 [6] is described as follows

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

where $\mathbf{\Phi}(i) = \mathbf{F}(t_i)\Delta t + \mathbf{I}$, $\mathbf{\Gamma}(i) = \mathbf{G}(t_i)\Delta t$, 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 [6] 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: $\langle \mathbf{v}(k) \rangle = \mathbf{0}$; $\langle \mathbf{v}(i)\mathbf{v}^T(j) \rangle = \mathbf{P}_\mathbf{v}(i,j)$;

3) State vector: $\langle \mathbf{z}(0) \rangle = \mathbf{m}_z(0)$; $\langle \mathbf{z}(0)\mathbf{z}^T(0) \rangle = \mathbf{P}_\mathbf{z}(0)$.

The **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

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

4.2 Dynamic Reconstruction

The problem is to design an optimal decision procedure that, when applied to all reconstructed MRS 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

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

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

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

and the prognosis of the mean-value becomes $\mathbf{m}_\mathbf{z}(i+1) = \mathbf{\Phi}\hat{\mathbf{z}}(i)$. 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 $\{\hat{\mathbf{B}}(0), \hat{\mathbf{B}}(1), ..., \hat{\mathbf{B}}(i-1)\}$ 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

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

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 [6] to solve (12) with respect to the state vector $\mathbf{z}(t)$ and taking into account the a priori information, the dynamic solution for the RSS state vector becomes

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

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

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

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

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

Here, the initial condition $\hat{\mathbf{\Lambda}}(0) = \Lambda\{\hat{\mathbf{B}}(0)\}$. 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.

4.3 Big-Data Technique

The optimal filtering procedure for dynamic reconstruction described by (15) will be implemented for MRS scenes using the Apache Hadoop software library [8], which is a framework that allows distributed processing of large data sets across clusters of computers using simple programming models.

5. SIMULATIONS

A RSS map is extracted from a set of multitemporal SPOT-5 images using the WPS method. Three level of RSS are selected:

– Black regions represents the RSS that relate to the humid zones of the MRS image.

– Dark-gray regions represents the RSS that relate to the dry zones of the MRS image.

– Light-gray regions represents the RSS that relate to the wet zones of the MRS image.

Figure 1 shows the original high-resolution scene (*1024x1024*-pixels, RGB image) corresponding to a dam within the State of Jalisco in Mexico. Figure 2 shows the RSS map obtained with the WPS method for the adopted ordered weight vector.

Figure 1. Original MRS scene.

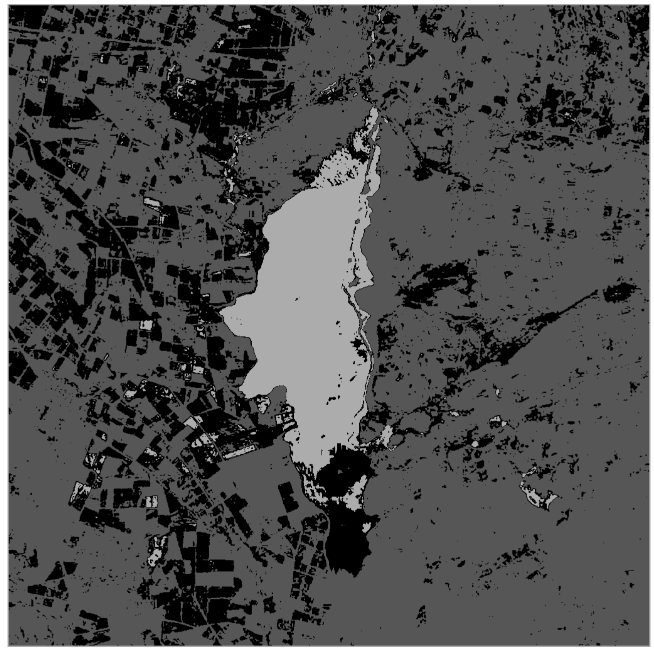

Figure 2. RSS map extracted with WPS for MDA analysis.

6. CONCLUDING REMARKS

A dynamical approach for solving the inverse problems of high-resolution dynamical reconstruction of MRS images is presented via processing the finite-dimensional and space-time measurements of the available sensor data. The dynamical RSS post-processing scheme reveals a 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, the dynamical post-processing and the employment of big-data techniques for processing. The results are indicative of a usefulness of the proposed approach for monitoring physical environmental characteristics, and those could be addressed for different environmental resource management applications. Nevertheless, the processing of several RSS maps extracted from MRS scenes with the application of the derived MDA framework in order to increase its accuracy is a matter of further analysis.

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