URBAN KNOWLEDGE ANALYSIS FOR DYNAMIC FORECASTING USING MULTISPECTRAL DATA

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ABSTRACT

The analysis of dynamical models for urban knowledge analysis using the information extracted from a geographical region processed from the data provided by multispectral remote sensing systems provides useful information for urban planning and resource management. However, several topics of interest on this particular matter are still to be properly studied. Using the remote sensing data that has been extracted from multispectral images from a particular geographic region in discrete time, its dynamic study is performed in both, spatial resolution and time evolution, in order to obtain the dynamical model of the physical variables and the evolutionary information about the data. This provides a background for understanding the future trends in development of the dynamics inherent in the multispectral and high-resolution images. This proposition is performed via an intelligent computational paradigm based on the use of dynamical filtering techniques modified to enhance the quality of reconstruction of the data extracted from multispectral remote sensing images and using high-performance computational techniques to unify the available data scheme with its dynamic analysis and, therefore, provide a behavioral model of the sensed data.

Index Terms— urban knowledge, dynamical analysis, remote sensing, image processing, multispectral analysis.

1. INTRODUCTION

Dynamic is a term that refers to a phenomenon that produces time changing patterns, the characteristics of that pattern at a particular time is related with those at other times. The term is nearly synonymous with time evolution or pattern of change [1].

Nearly all the observed phenomena every day, or in a scientific research, have important dynamic aspects. Many dynamic systems can be understood and analyzed intuitively without resort to mathematics and without development of a general theory of dynamics. However, in order to approach unfamiliar complex situations efficiently, it is necessary to proceed systematically. Mathematics can provide the required economy of language and conceptual framework; therefore, the term dynamics takes a dual meaning. It is a term for the time evolution phenomenon in the real world, and a term for that part of mathematical science that is used for its representation and analysis [1].

Dynamic systems are represented mathematically in terms of either differential or difference equations. These equations provide the structure for representing time linkages among variables.

2. PROBLEM MODEL

An innovative paradigm that has been developed is presented, its objective is the mathematical analysis of the dynamical model in both, spatial resolution and time evolution, of a particular geographical region obtained from multispectral remote sensing data (MRSD) in discrete time. This is performed via the Multispectral Dynamic Forecasting (MDF) method, which unifies the MRSD mapping scheme with its dynamic analysis to provide a high-resolution mapping of the MRSD in discrete time. If the attributes of interest of a system are changing in time, then it is referred to as a dynamic system. A MDF process provides the mathematical model of change in space resolution and time evolution of such a dynamic system [2].

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 $u=Se+n$ ($e \in \mathrm{E}$; $u,n \in \mathrm{U}$; $S\text{:}\mathrm{E} \rightarrow \mathrm{U}$) 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 MRSD 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 $\boldsymbol{\rho}\in P$ and azimuth angle $\boldsymbol{\theta}\in\Theta$ domains, $\mathbf{x}=(\boldsymbol{\rho},\boldsymbol{\theta})^T$, $\mathbf{X}=P\times\Theta$, respectively. The MRSD 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 MRSD methodology, any particular MRSD of interest is to be extracted from the reconstructed MRS image $\hat{B}(\mathbf{x})$ applying the so-called signature extraction operator Λ [3].

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

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

The signature reconstruction problem is formulated as follows: to map the reconstructed particular MRSD of interest $\hat{\Lambda}(\mathbf{x})=\mathit{\Lambda}(\hat{B}(\mathbf{x}))$ 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. MULTISPECTRAL DYNAMIC FORECASTING

3.1 Lineal Dynamic Model

The crucial issue in application of the modern dynamic filter theory to the problem of reconstruction of the desired MRSD 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 MRSD in time [4] its dynamical model can be represented in a vectorized space-time form defined by a stochastic differential state equation of the first order

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

where $\mathbf{z}(t)$ is the so-called model state vector, $\mathbf{C}$ defines a linear operator that introduces the relationship between the MRSD 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 $\langle\boldsymbol{\xi}(t)\boldsymbol{\xi}^T(t')\rangle=\mathbf{P}_{\xi}(t)\delta(t-t')$ [4]. Here, $\mathbf{P}_{\xi}(t)$ is referred to as state model disperse matrix [4] 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 $\mathbf{B}(t)$ and the desired MRSD map $\boldsymbol{\Lambda}(t)$ represented as

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

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

The aim of the dynamic filtration is to find an optimal estimate of the desired MRSD $\hat{\boldsymbol{\Lambda}}(t)=\mathbf{C}\hat{\mathbf{z}}(t)$ 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 MRSD 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 MRSD 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 [5] 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 $\boldsymbol{\Phi}(i)=\mathbf{F}(t_i)\Delta t+\mathbf{I}$, $\boldsymbol{\Gamma}(i)=\mathbf{G}(t_i)\Delta t$, and Δt represents the time sampling interval for dynamical modeling of the MRSD in discrete time.

The statistical characteristics of the a priori information in discrete-time [5] are specified as

1) Generating noise: $\langle\boldsymbol{\xi}(i)\rangle=\mathbf{0}$; $\langle\boldsymbol{\xi}(i)\boldsymbol{\xi}^T(j)\rangle=\mathbf{P}_{\xi}(i,j)$;

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 $\mathbf{0}$ 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

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

3.2 Dynamic Reconstruction

The problem is to design an optimal decision procedure that, when applied to all images $\{\hat{\mathbf{B}}(i)\}$ in discrete time i ($i_0\rightarrow i$), provides an optimal solution to the desired MRSD 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

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

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. Thus, the dynamical estimation strategy is modified to

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

For the evolution $(i+1)$-st discrete time prediction/estimation step, the dynamical MRSD 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 [5] 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 MRSD state vector becomes

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

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 MRSD 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 MRSD model (6).

4. SIMULATIONS

In the simulation results, a set of 40 MRSD maps were extracted from multispectral remote sensing images with high-resolution values for of spectral and spatial resolution and for a particular geographical scene. The MDF methodology is applied to the collection of MRSD maps [6].

First, the collection of MRSD maps [4] extracted in different times (discrete) for the same scene is set for the simulation. Therefore, the discrete evolution time κ equals to 40. Second, the pixel evolution vector $\mathbf{\Sigma}_{ij}$ is defined for this simulation as

$$\mathbf{\Sigma}_{ij}=\left(\hat{\mathbf{\Sigma}}_{ij,1}\quad\hat{\mathbf{\Sigma}}_{ij,2}\quad\ldots\quad\hat{\mathbf{\Sigma}}_{ij,40}\right), \quad (16)$$

where $\hat{\mathbf{\Sigma}}$ represents the threshold values of the same (i, j)-th pixel from the MRSD maps. This is the observation signal to be post-processed with the dynamic post-processing method. Third, the measurement matrix $\mathbf{H}$ and the state transition matrix $\mathbf{\Phi}$ are simplified to $\mathbf{I}$ because the equation of observation and the stochastic dynamic state equation are supposed to be ideal (noiseless, because the observation vector is directly extracted from the MRSD maps). The dynamic filter operator (gain matrix) $\mathbf{\Theta}$ determines the variance evolution of the observation values (16) of the dynamically reconstructed MRSD. The initial conditions are the initial observation value $\mathbf{\Sigma}(0)$ and its initial estimation.

The MDF method specified by equation (15) is applied to estimate the ultimate value $\hat{\mathbf{\Lambda}}$ that is the next $(\kappa+1)$-*st* continuous time step of the observation vector $\mathbf{\Sigma}_{ij}$. This process is performed through all the $\{(i, j)\}$ pixels of the MRSD maps to obtain a single aggregated MRSD map $\hat{\mathbf{\Lambda}}_{MDF}$. The simulation results of application of the developed MDF method are presented in Figures 1 and 2. Figure shows the first MRSD map (*1024x1024*-pixels) extracted from the first remote sensing scenes that corresponds to the metropolitan area of the city of Guadalajara, in Mexico. This is performed in different time (κ = *1,2,3,4, ...*) for the time evolution analysis, respectively.

Figure 2 shows the dynamic MRSD map reconstructed with the application of the MDF method for the $(\kappa+1)$ time step $(\kappa=41)$ specified by model (15). The MRSD map were reconstructed in a discrete time κ, therefore, the MDF method produces the desired dynamic MRSD prediction for the next discrete time step $(\kappa+1)$, which represents the prediction of changes.

5. CONCLUDING REMARKS

From the presented simulations results, it is possible to deduce that the developed MDF method provides a possibility to perform the intelligent analysis of the dynamic behavior or the desired environmental map in both, spatial resolution and time evolution.

Figure 1. MRSD map from the RS scene for $\kappa = 1$ discrete time.

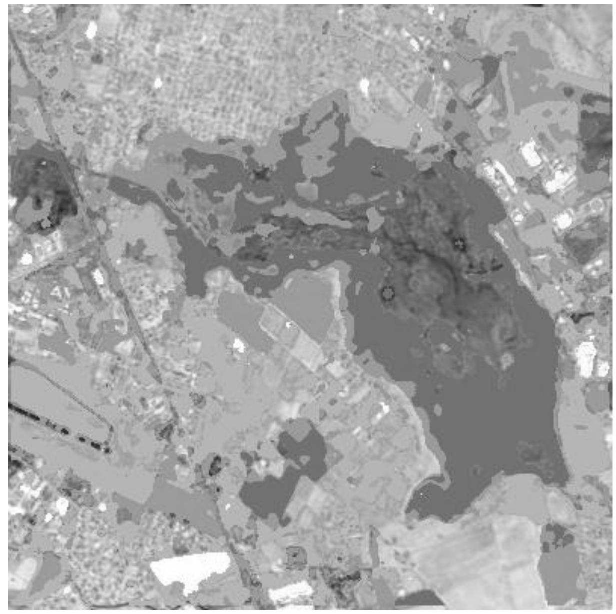

Figure 2. Dynamic prediction obtained with the MDF method for $\kappa = 41$ discrete time.

This is achieved because the MDF algorithm aggregates the information of the MRSD collection of remote sensing images for a particular geographical region in discrete time, and employs more detailed robust a priori information from the original reconstructed remote sensing scene. The resulting dynamic MRSD prediction map ensures a high accuracy in the estimation process and in the classification achieved.

A real-time process (RTP) can be defined as the study of software systems which are subject to a real-time constraint. By contrast, a non-real-time system is one for which there is no deadline, even if fast response or high performance is desired or even preferred. The needs of RTP software are often addressed in the context of real-time operating systems, and synchronous programming languages, which provide frameworks on which to build RTP application software. A RTP may be one where its application can be considered (within context) to be mission critical. Moreover, RTP can be said to have failed if they are not completed before their deadline, where their deadline is relative to an event. A deadline must be met, regardless of system load.

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