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Dynamical Post-Processing of Environmental Electronic Maps Extracted from Large Scale Remote Sensing Imagery

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Abstract **– A new intelligent computational paradigm based on the use of dynamical filtering techniques modified to enhance the quality of reconstruction of physical characteristics of environmental electronic maps extracted from the large scale remote sensing imagery is proposed. A robust Kalman filter-based algorithm is developed for the analysis of the dynamic behavior of hydrological indexes extracted from the real-world remotely sensed scenes. The simulation results verify the efficiency of the proposed approach as required for decision support in environmental resources management.**

Keywords – remote sensing; dynamic filtration; classification; decision support; environmental resource management

I. INTRODUCTION

Intelligent post-processing of the environmental monitoring data is now a mature and well developed research field, presented and detailed in many works (see, for example [1] thru [9] and 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 different environmental characteristics for decision support applications. In this study, we undertake an attempt to develop and verify via computational simulations a new robust filtering method that provides the possibility to track, filter and predict the dynamical behavior of the physical characteristics extracted from the real-world remote sensing imagery.

II. 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 $u=Se+n$ ($e \in \mathrm{E}$; $u,n \in \mathrm{U}$; $S:\mathrm{E} \rightarrow \mathrm{U}$) in the L_2 Hilbert signal spaces E and U [1] with the metric structures induced by inner products,

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

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

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

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 remote sensing (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 $\rho \in P$ and azimuth angle $\theta \in \Theta$ domains, $\mathbf{x}=(\rho,\theta)^{\mathrm{T}}$, $\mathbf{X}=P \times \Theta$, 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], [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 physical remote sensing signature (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.

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

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Taking into account the remote sensing signature (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∍$\mathbf{x}$ via post-processing (4) whatever values of the reconstructed scene image $\hat{B}(\mathbf{x})$, $\mathbf{x}\in X$ are available.

III. Image Segmentation And Classification

For this particular study, covered water, humid and dry zones are analyzed as particular RSS of interest. We consider the so-called hydrological electronic maps (HEM), extracted via fusion of the weighted order statistics (WOS) method [6] with the minimum distance to mean (MDM) methodology [7].

The WOS is a methodology that can be considered as a generalization of the median filtering, where the information of all the order statistics is combined to provide an improved estimate of a variable [6]. The MDM decision rule is based on minimum distance classification of the mean values of a given set of pixels [7]. The fused WOS-MDM algorithm provide an accurate segmentation and classification for a particular physical index extracted from the reconstructed RSS.

IV. Dynamical HEM Computing

A. 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 evolution time is related to modeling of the RS as a random field (spatial map developing in evolution time t) that satisfies some dynamical state equation. Following the typical linear assumptions for the development of the RSS in evolution time [8], [9], 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 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 $\langle \boldsymbol{\xi}(t)\boldsymbol{\xi}^T(t') \rangle = \mathbf{P}_{\xi}(t)\delta(t-t')$ [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 evolution 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 $\Lambda(t)$ can now be represented [8] in the following form

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

where $\mathbf{L}$ is the linearized approximation (i.e. first order matrix-form approximation [9]) 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 [8], [9] to reconstruct the desired RSS in evolution 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 evolution 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 [9] 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 RSS in discrete time. The statistical characteristics of the a priori information in discrete-time [8] 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 [9]

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

B. 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 ($i_0 \to i$), 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 ($i_0 \to i$) is represented as

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

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

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

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, i.e.

$$\mathbf{m}_\mathbf{z}(i+1) = \mathbf{\Phi}\left\langle \mathbf{z}(i) \middle| \hat{\mathbf{B}}(0), \hat{\mathbf{B}}(1),..., \hat{\mathbf{B}}(i) \right\rangle + \mathbf{\Gamma}\langle \xi(i) \rangle = \mathbf{\Phi}\hat{\mathbf{z}}(i) \qquad (10)$$

where the prognosis of the mean-value becomes $\mathbf{m}_\mathbf{z}(i+1) = \mathbf{\Phi}\hat{\mathbf{z}}(i)$. From (8) thru (10) one may 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, using these derivations, the dynamical estimation strategy is modified to one-step optimal prediction procedure

$$\hat{\mathbf{z}}(i+1) = \left\langle \mathbf{z}(i+1) \middle| \hat{\mathbf{z}}(i); \hat{\mathbf{B}}(i+1) \right\rangle = \left\langle \mathbf{z}(i+1) \middle| \hat{\mathbf{B}}(i+1); \mathbf{m}_\mathbf{z}(i+1) \right\rangle, \qquad (11)$$

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

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

with the a priori predicted mean (9) for the desired state vector. Applying the Wiener minimum risk strategy [9] 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

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

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

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

Using the derived filter equations (13) and (14) and the initial RSS state model given by (6), the optimal filtering procedure for dynamic reconstruction of the desired RSS map in the evolution discrete time becomes

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

with 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.

V. Simulations

In this section, we present some results of the simulation experiment indicative of the enhanced quality of dynamical RSS reconstruction with the proposed approach. These are reported for RS scene borrowed from the real-world imagery of the Metropolitan area of Guadalajara city in Mexico [10].

Fig. 1 shows the original scene image formed with the high-resolution synthetic aperture radar (SAR) [10]. Fig. 2 thru Fig. 4 present the HEMs extracted using the WOS, MDM and the fused WOS-MDM algorithms, respectively, applying the classification operator (3). Such HEMs are specified as 2-bit 512x512 pixel hydrological RSS that classify the areas in the reconstructed scene images $\hat{B}(\mathbf{x})$ into four classes: areas covered with water (black zones in the figures), the humid areas (heavy-gray zones), the dry areas (light-gray zones), and non classified regions (white zones). The fused WOS-MDM algorithm segments and classifies the RS scene and provides a HEM that is highly-accurate compared with the in-site a priori information model.

Fig. 5 and Fig. 6 shows the results of the dynamical HEM post-processing for two discrete-time evolution models, obtained with the application of the derived algorithm (15). These simulations present the evolution in time of the physical characteristics specified via the HEMs and displayed in Fig. 2 thru Fig. 4. Darker zones represent the filtered change behavior of the HEMs in their discrete-time evolutions. The analysis and interpretation of these results require more investigation and are the matter of further studies.

VI. Concluding Remarks

In this paper, we have presented the dynamical approach for solving the nonlinear inverse problems of high-resolution dynamical reconstruction of the RSS of the environmental scenes via processing the finite-dimensional space-time measurements of the available sensor data.

We have developed the dynamical RSS post-processing scheme that reveals some possible approach toward a new dynamic computational paradigm for high-resolution fused numerical reconstruction and filtration of different RSS maps in evolution time. The presented study establishes the foundation to assist in understanding the basic theoretical and computational aspects of RS image enhancement, extraction of physical scene characteristics and their dynamical post-processing.

The study was undertaken in a context of RS data processing as required for large scale RS scene analysis, although, the results can be extended to other research areas in intelligent sensor systems design and applications.

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 high resolution SAR scene image.

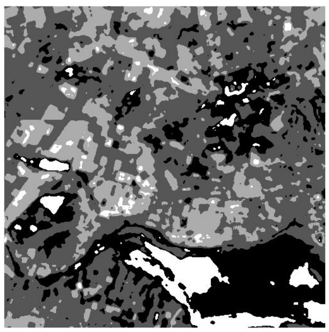

Figure 2. HEM extracted from the original high resolution SAR scene applying the WOS method.

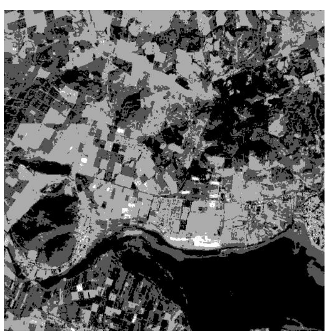

Figure 3. HEM extracted from the original high resolution SAR scene applying the MDM method.

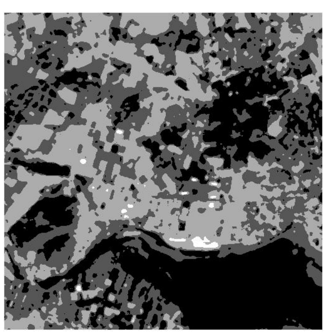

Figure 4. HEM extracted from the original high resolution SAR scene applying the fused WOS-MDM algorithm.

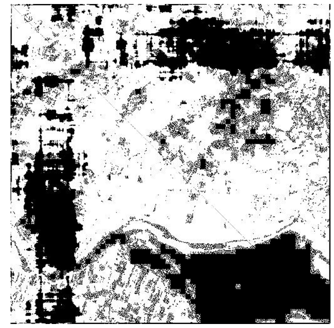

Figure 5. Dynamics in the HEM evolution filtred from Fig. 2: darker zones represents the areas that have been changed with the evolution.

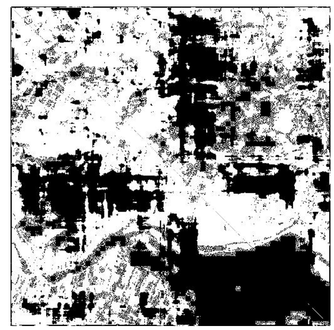

Figure 6. Dynamics in the HEM evolution filtred from Fig. 3: darker zones represents the areas that have been changed with the evolution.

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