Dynamical Enhancement of the Large Scale Remote Sensing Imagery for Decision Support in Environmental Resource Management

Yuriy V. Shkvarko, CINVESTAV, Unidad Guadalajara, Av. Cientifica 1145, Colonia El Bajío, 45010, Zapopan, Jalisco, Mexico; E-mail: shkvarko@gdl.cinvestav.mx

Ivan E. Villalon-Turrubiates, CINVESTAV, Unidad Guadalajara, Av. Cientifica 1145, Colonia El Bajío, 45010, Zapopan, Jalisco, Mexico; E-mail: villalon@gdl.cinvestav.mx

ABSTRACT

In this study, we address a new efficient robust optimization approach to large-scale environmental RSSS reconstruction/enhancement as required for remote sensing imaging with multi-spectral array sensors/SAR. First, the problem-oriented robustification of the previously proposed fused Bayesian-regularization (FBR) enhanced imaging method is performed to alleviate its ill-poseness due to system-level and model-level uncertainties. Second, we incorporate the dynamic filtration paradigm into the overall reconstruction technique to enhance the quality of the imagery as it is required for decision support in environmental resource management with dynamic RSSS behavior.

Keywords: Environmental Remote Sensing, Dynamic Filtration, Resource Management, Decision Support, Regularization.

I. INTRODUCTION

Nonlinear reconstructive processing/enhancement of large-scale environmental imagery provided with modern multi-spectral array sensors/synthesized array sensors/radar (SAR) are extremely computation and time consuming. The crucial aspects here are problem-level and system-level model uncertainties that complicate severely the implementation of any adaptive nonlinear large-scale image enhancement techniques based on descriptive or statistical regularization paradigms [1] - [4]. The aggregated regularization inference-based treatment of the problem was initially undertaken in [3] and developed in recent papers [7], [8] in the scope of the inverse problem methodology for coherent SAR image restoration. Some recent publications in this field use the maximum entropy (ME) approach but again in a context of descriptive regularization that simply alleviates the ill-posed nature of the corresponding scattering pattern estimation or image restoration inverse problems [5].

The key distinguishing feature of the new paradigm considered in the present study is that the inverse problem of estimating the particular remote sensing scene signatures (RSS) from the available measurements of random realizations of the data field is stated and treated in the framework of the robust regularization strategy aggregated with the dynamic filtration. We address a new efficient robust optimization approach to large-scale environmental RSS reconstruction/enhancement as required for remote sensing imaging with multi-spectral array sensors/SAR. First, the problem-oriented robustification of the previously proposed descriptive regularization (DR) enhanced imaging method is performed to alleviate its ill-poseness due to system-level and model-level uncertainties. Second, we incorporate the dynamic filtration paradigm into the overall reconstruction technique to enhance the quality of the imagery as it is required for decision support in environmental resource management with dynamic RSS behavior. The new proposed method is addressed to as the dynamical aggregated robust regularization (DARR) technique. Finally, we report and discuss some simulation results of enhancement of the real-world 1024-by-1024-pixel format 256-scaled environmental RSS indicative of the efficiency of the developed DARR method. In the simulations, the advantage of the RSS reconstruction using the derived DARR-optimal and suboptimal estimators over the case of the conventional matched spatial processing technique [6] based on the use of the matched spatial filtering method is evident. The resolution is substantially improved; regions of interest and distributed object boundaries are much better defined, while ringing effects usually observed with filters based on inverse operations are substantially reduced.

II. PROBLEM PHENOMENOLOGY

According to the mathematical statement [1], [2], [4] to perform the image enhancement via processing the remote sensing data employing the descriptive regularization (DR) approach one have to solve the optimization problem

$$\hat{\mathbf{v}} = \underset{\mathbf{v}}{\operatorname{argmin}}\, E(\mathrm{v}\,|\lambda) = \underset{\mathbf{v}}{\operatorname{argmin}}\, \{(1/2)\, \lambda_1 J_1(\mathrm{v}) + (1/2)\lambda_2 J_2(\mathrm{v})\} \qquad (1)$$

of minimizing the cost (energy) function $E(\mathrm{v}|\lambda)$ with respect to the desired K-D image vector v for the assigned (or adjusted) values of the regularization parameters $\lambda = (\lambda_1, \lambda_2)^T$. The proper selection of λ is associated with parametrical optimization of the DR process. In (1), $J_1(\mathrm{v}) = ||\mathrm{u} - \mathrm{Fv}||^2$ represents the error function for corresponding sensing system, and $J_2(\mathrm{v})$ represents the conventional Tikhonov's stabilizer [5].

The data acquisition model is defined, as in [7], by the equation, $\mathrm{u} = \mathrm{Fv} + \mathrm{n}$ where F defines the corresponding system's degradation operator usually referred to as the imaging system point spread functions (PSF) and n represents the noise in the actually acquired image, respectively.

Next, the particular RSS is formed applying corresponding nonlinear signature extraction operator Φ to the enhanced image $\hat{\mathbf{v}}$, i.e.

$$\hat{\mathbf{E}} = \Phi\,(\,\hat{\mathbf{v}}\,)\,. \qquad (2)$$

Note, that in our particular study of the hydrological RSS, the Φ is specified as corresponding weighted order statistics (WOS) computing operator [1].

It is important to mention that the DR solutions for $\hat{\mathbf{v}}$ and $\hat{\mathbf{E}}$ exist and are guaranteed to be unique for a given λ because the surfaces of all functions that compose E(v|λ) given by (1) are convex. But one can deduce that in the case of incorporating any additional dynamic information on the evolution of the RSS $\hat{\mathbf{E}}$ in time, the non-linearity of the aggregated optimization problem (1), (2) will require extremely complex computations and will result in the technically intractable scheme if solve this problem employing the standard direct minimization techniques [1], [3]. For this reason, we propose here to apply the iterative computing paradigm for implementing the proposed DARR method.

III. DYNAMIC RSS RECONSTRUCTION WITH DARR METHOD

The crucial issue in application of the modern dynamic filter theory [1] to the problem of reconstruction of the desired RRS in current time is related to modeling of the RSS as a random field (i.e. spatial map developing in discrete time i) that satisfies the dynamical difference state equation [1]

$$\mathbf{z}(i+1) = \mathbf{\ddot{O}}(i)\mathbf{z}(i) + \mathbf{\tilde{A}}(i)\mathbf{x}(i)$$
$$\mathbf{\ddot{E}}(i) = \mathbf{C}(i)\mathbf{z}(i) \tag{3}$$

specified by the linear dynamic model formation operators (matrices) $\mathbf{\ddot{O}}(i)$, $\mathbf{\tilde{A}}(i)$ and $\mathbf{C}(i)$, respectively. The dynamical estimation strategy for such optimal RSS prediction procedure can now be defined as follows [1]

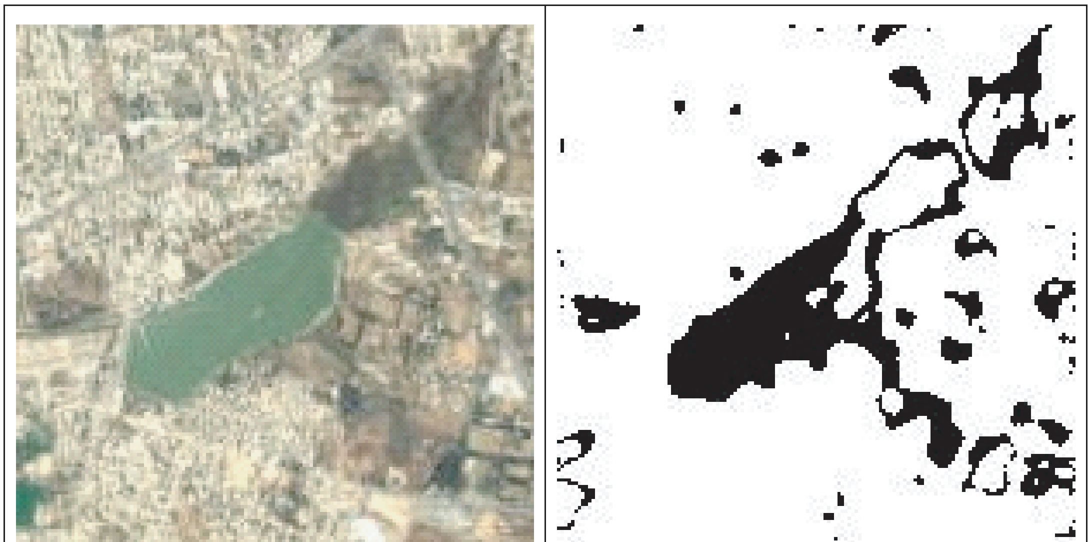
$$\hat{\mathbf{z}}(i+1) = \langle \mathbf{z}(i+1) | \hat{\mathbf{z}}(i)\ \hat{\mathbf{v}}(i+1) \rangle\ ;$$
$$\mathbf{\ddot{E}}(i) = \mathbf{C}(i)\mathbf{z}(i) \tag{4}$$

Routinely solving the dynamical RSS filtration problem (4) for the current (i+1)-st discrete-time prediction-estimation step, we obtain the desired DARR technique

$$\hat{\mathbf{z}}(i+1) = \mathbf{m}_z(i+1) + \mathbf{\acute{O}}(i+1)\left[\hat{\mathbf{v}}(i+1) - \mathbf{H}(i+1)\mathbf{m}_z(i+1)\right]\ ;$$
$$\mathbf{\ddot{E}}(i) = \mathbf{C}(i)\mathbf{z}(i) \tag{5}$$

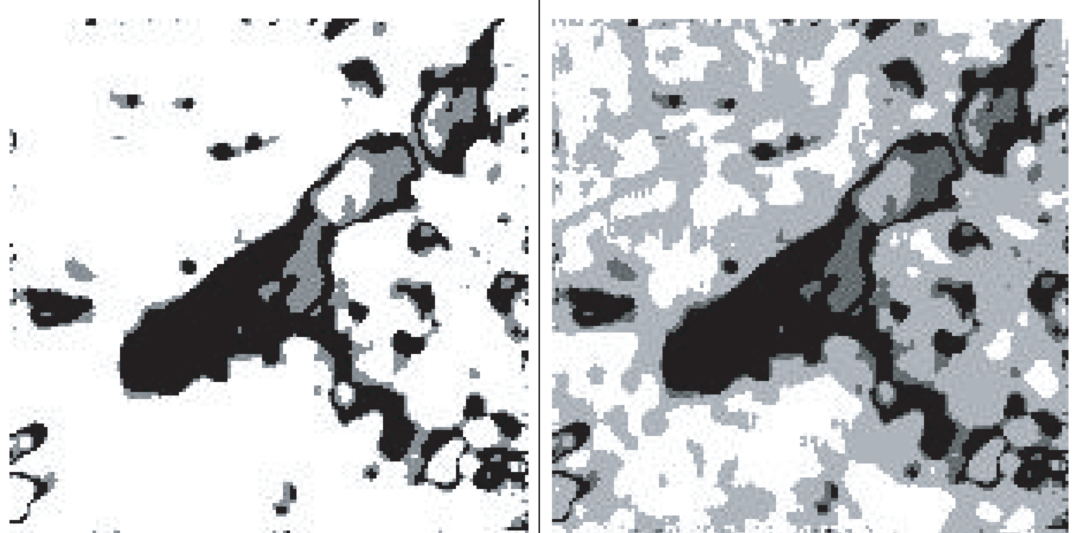
where $\mathbf{m}_z(i+1)$ represents the predicted mean vector and the optimal dynamic filter operator $\mathbf{\acute{O}}(i+1)$ is defined as follows,

Figure 1. Simulation results of hydrologic electronic map (HEM) extraction from the original super-high-resolution image reconstructed with the proposed DARR method.



(a) – Original super-high-resolution image.

(b) – HEM-W extracted from the original scene image reconstructed with the proposed DARR method.



(c) – HEM-WH extracted from the original scene image reconstructed with the proposed DARR method.

(d) – HEM-WHD extracted from the original scene image reconstructed with the proposed DARR method.

$$
\begin{aligned}
&\acute{\mathbf{O}}(i+1) = \mathbf{K}_{\acute{o}}(i+1)\mathbf{H}^{T}(i+1)\mathbf{P}_{\acute{\imath}}^{-1}(i+1)\ ;\\
&\mathbf{K}_{\acute{o}}(i+1) = \left[\text{\O}_{\acute{o}}(i+1) + \mathbf{P}_{z}^{-1}(i+1)\right]^{-1}\ ;\\
&\text{\O}_{\acute{o}}(i+1) = \mathbf{H}^{T}(i+1)\mathbf{P}_{\acute{\imath}}^{-1}(i+1)\mathbf{H}(i+1)\ .
\end{aligned}
\qquad (6)
$$

Last, using the derived filter equations (4), (5), we finally obtain the DARR optimal filtering procedure for dynamic reconstruction of the desired RSS map in the current discrete time $i = 0, 1, \ldots$

$$
\ddot{\mathbf{E}}(i+1) = \ddot{\mathbf{O}}(i)\hat{\mathbf{z}}(i) + \acute{\mathbf{O}}(i+1)\left[\hat{\mathbf{v}}(i+1) - \mathbf{H}(i+1)\ddot{\mathbf{O}}(i)\hat{\mathbf{z}}(i)\right];\ i = 0, 1, \ldots \quad (7)
$$

with the initial condition, $\ddot{\mathbf{E}}(0) = \Lambda\{\hat{\mathbf{B}}(0)\}$. The crucial issue to note here is related to model uncertainties regarding the particular employed dynamical RSS model (2), hence the corresponding uncertainties regarding the overall dynamically reconstructed RSS (7). These issues require more investigations and are the matter of further studies.

V. SIMULATION EXPERIMENT AND DISCUSSION

The results of the simulation experiment are summarized in Figure 1. The Figure 1.a shows the original super-high-resolution image, displaying the dam named "Las Pintas" in the Metropolitan area of Guadalajara in Mexico.

In Figure 1.b, 1.c and 1.d we present the simulation results of dynamic reconstruction-filtration of a particular RSS that represents the so-called *Hydrologic Electronic Map* (**HEM**) extracted from the reconstructed images { $\hat{\mathbf{v}}$ }. The HEMs are specified as follows:

1. **HEM-W** (Water content) map that represents the water content zones extracted from the original super-high-resolution image reconstructed with the proposed DARR method. The watered zones are shown in black. All white regions represent non-classified zones.
2. **HEM-WH** (Water and humidity content) map that represents the water content zones (black regions) and the humidity content zones (gray region) extracted from the original super-high-resolution image reconstructed with the proposed DARR method. All white regions represent non-classified zones.
3. **HEM-WHD** (Water, humidity and dry content) map that represents the water content (black region), the humidity content zones (gray region) and the dry content zones (gray region) extracted from the original super-high-resolution image reconstructed with the proposed DARR method. All white regions represent non-classified zones.

The purpose of this research was to investigate the possibility to perform the dynamic RSS filtering in the realistic conditions of minimum prior model knowledge regarding the dynamical behavior of the particular RSS. The dynamic HEM information was used iteratively applying the DARR algorithm (5), (6), (7).

The reported results qualitatively demonstrate that with proper adjustment of the degrees of freedom in the general DARR algorithm (5), (6), (7), it is possible to predict the dynamic behaviour of the HEMs. The detailed investigation of application of the developed DARR method to resource management is the matter of the perspective studies.

V. CONCLUDING REMARKS

In this paper, we have presented the dynamical aggregated robust regularization (DARR) approach for solving the nonlinear inverse problems of high-resolution dynamical reconstruction of the SSP and RSS of the remotely sensed scenes via processing the finite-dimensional space-time measurements of the available sensor system signals as it is required, for example, for enhanced RS imaging/scene mapping with imaging radar/SAR. 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 current time. In future work, we intend to develop a family of such dynamical versions of the DARR-based algorithms for updating the relevant RSS maps in current discrete time.

REFERENCES

[1] H.H. Barret and K.J. Myers, *Foundations of Image Science*, New York: Willey, 2004.

[2] R.N. McDonough, *Nonlinear Methods of Spectral Analysis*, S. Haykin, 1984.

[3] E. Dadgeon and R.M. Mersereau*, Multidimensional Digital Signal Processing*, N.J.: Prentice Hall Inc., 1984.

[4] J. Munier, and G.L. Delisle, "Spatial analysis in passive listening using adaptive techniques", in *Proc. IEEE*, 1987, vol. 75.

[5] D. Ingman and Y. Merlis, "Maximum entropy signal reconstruction with neural networks", *IEEE Trans. Neural Networks*, vol. 3, pp. 195-201, 1992.

[6] Raney R.K., *Principles and Applications of Imaging Radar, Manual of Remote Sensing,* New York: John Wiley & Sons, 1998.

[7] Y. V. Shkvarko, "Unifying regularization and Bayesian estimation methods for enhanced imaging with remotely sensed data Part I: Theory", *IEEE Trans. on Geoscience and Remote Sensing*, pp. 923-931, 2004.

[8] Y. V. Shkvarko, "Unifying regularization and Bayesian estimation methods for enhanced imaging with remotely sensed data Part II: Implementation and performance issues", *IEEE Trans. on Geoscience and Remote Sensing*, pp. 932-940, 2004.

Related Content