Cognitive Reconstructive Remote Sensing for Decision Support in Environmental Resource Management

Ivan E. Villalon-Turrubiates, *Member, IEEE*, and **Yuriy V. Shkvarko**, *Senior Member, IEEE*
CINVESTAV, Unidad Guadalajara
Av. Científica 1145, Colonia El Bajío, C.P. 45010, Zapopan Jalisco, MEXICO
Telephone: (+5233) 37703700, Fax: (+5233) 37703709, E-mail: villalon@gdl.cinvestav.mx

***Abstract* – In this paper, the problem of reconstruction of different characteristic signatures (CSs) of the monitored environmental scenes from the multi-spectral remotely sensed data is cast in the unified framework of the statistically optimal Bayesian inference making strategy aggregated with the proposed cognitive descriptive regularization paradigm. The reconstructed CS maps are then treated as sufficient statistical data required for performing the environmental resource management tasks. Simulation examples with the real-world remote sensing data are provided to illustrate the efficiency of the proposed approach.**

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

I. INTRODUCTION

In the environmental resource management applications [4], the estimates of different environmental CSs [8], [9], [10] constitute the statistical data of interest used to perform the management support tasks. In view of this, we refer to the initial stage of the decision support problem as a problem of high-resolution and high-quality reconstruction of the CSs from a set of available measurements of the multi-sensor/multi-spectral data. In principal, we propose a new approach to reconstructive imaging and mapping of different CSs stated and mathematically treated as statistical nonlinear ill-conditioned inverse problems. The descriptive regularization (DR) based investigation of such class of problems was originally undertaken in [1], [4] and developed in recent papers [6], [7] in the scope of the robust regularization methodology. Some recent publications in this field employ the information theory-based approaches [7], [12] but all those are again developed within the DR methodology that simply alleviates the ill-posed nature of the corresponding pattern estimation or scene reconstruction inverse problems [11].

The key distinguishing feature of a new approach proposed in the present study is that the problems of reconstructive multi-sensor imaging and CSs mapping are treated in the unified framework of the statistically optimal Bayesian minimum risk (MR) strategy aggregated with the proposed new cognitive DR paradigm. The advantage of the environmental mapping and feature extraction employing the developed fused MR-DR method over the case of the conventional spatial processing with the use of different previously proposed regularization techniques was verified through extensive simulations. The resolution and information content of different reconstructed CSs were substantially improved: regions of interest and distributed object boundaries of the reconstructed CSs were much better defined, while ringing effects were substantially reduced. The simulation examples illustrate enhanced overall performances attained with the proposed MR-DR method with the use of the real-world remote sensing imagery.

II. MR-DR METHOD

2.1. DR projection formalism for data representation

Viewing it as an approximation problem [2], [6] leads one to a projection concept for a reduction of the data wavefield $u(\mathbf{y})$ observed in a given space-time domain $Y \ni \mathbf{y}$ to the M-D vector $\mathbf{U}$ of sampled spatial-temporal data recordings. The M-D observations in the terms of projections [2], [7] can be expressed as

$$u_{(M)}(\mathbf{y}) = (P_{\mathrm{U}(M)}u)(\mathbf{y}) = \sum U_m \phi_m(\mathbf{y}) \qquad (1)$$

with coefficients $U_m = [u, h_m]_{\mathrm{U}}$; $m = 1, \ldots, M$, where $P_{\mathrm{U}(M)}$ denotes the projector onto the M-D observation subspace $\mathrm{U}_{(M)}$ that is uniquely defined by a set of the basis functions $\{\phi_m(\mathbf{y})\}$ that span $\mathrm{U}_{(M)}$. In analogy to (1), one can define the projection scheme for the K-D approximation of the scene scattering function over a given spatial image domain $X \ni \mathbf{x}$ as follows,

$$e_{(K)}(\mathbf{x}) = (P_{\mathrm{E}(K)}\, e)(\mathbf{x}) = \sum E_k \varphi_k(\mathbf{x}); \qquad (2)$$

$E_k = [e, g_k]_E$; $k = 1, \ldots, K$, where $P_{E(K)}$ defines a projector onto the K-D image subspace $E_{(K)}$ spanned by K basis functions $\{\varphi_k(\mathbf{x})\}$. The $\{\varphi_k(\mathbf{x})\}$ and $\{g_k(\mathbf{x})\}$ compose the dual bases in $E_{(K)}$, and the linear integral projector operator is specified by its kernel $P_{E(K)}(\mathbf{x}, \mathbf{x}') = \Sigma\, \varphi_k(\mathbf{x})\, g_k^*(\mathbf{x}')$.

2.2. Problem model

General model of the observation wavefield u is defined by specifying the stochastic equation of observation of an operator form [6]: $u = Se + n$; $e \in E$; $u, n \in U$; $S : E \to U$, in the Gilbert signal spaces E and U with the metric structures induced by the inner products, $[u_1, u_2]_U = \int_Y u_1(\mathbf{y}) u_2^*(\mathbf{y}) d\mathbf{y}$, and $[e_1, e_2]_E = \int_X e_1(\mathbf{x}) e_2^*(\mathbf{x}) d\mathbf{x}$, respectively. The operator model of the stochastic equation of observation (EO) in the conventional integral form [2], [4] may be rewritten as

$$u(\mathbf{y}) = (Se(\mathbf{x}))(\mathbf{y}) = \int_X S(\mathbf{y}, \mathbf{x})\, e(\mathbf{x}) d\mathbf{x} + n(\mathbf{y}). \tag{3}$$

Using the presented above DR formalism, one can proceed from the operator-form EO (3) to its conventional vector form,

$$\mathbf{U} = \mathbf{SE} + \mathbf{N}\,, \tag{4}$$

in which $\mathbf{E}$, $\mathbf{N}$ and $\mathbf{U}$ are the zero-mean vectors composed of the coefficients E_k, N_m, and U_m. These are characterized by the correlation matrices $\mathbf{R_E} = \mathbf{D} = \mathbf{D}(\mathbf{B}) = \mathrm{diag}(\mathbf{B})$, $\mathbf{R_N}$, and $\mathbf{R_U} = \mathbf{S}\mathbf{R}_E\mathbf{S}^+ + \mathbf{R_N}$, respectively. The vector, $\mathbf{B}$, is composed of the elements $B_k = \langle E_k E_k^* \rangle$; $k = 1, \ldots, K$, and is referred to as a K-D vector-form approximation of the Spatial Spectrum Pattern (SSP). We refer to the estimate $\hat{\mathbf{B}}$ as the discrete-form representation of the brightness image of the wavefield sources distributed in the environment remotely sensed with the array radar (SAR), in which case the continuous-form finite dimensional approximation of the estimate of the SSP distribution $\hat{B}_{(K)}(\mathbf{x})$in the environment in a given spatial image domain $X \ni \mathbf{x}$ can be expressed as follows,

$$\hat{B}_{(K)}(\mathbf{x}) = \Sigma\, B_k |\varphi_k(\mathbf{x})|^2 = \boldsymbol{\varphi}^{\mathrm{T}}(\mathbf{x})\mathrm{diag}(\hat{\mathbf{B}})\boldsymbol{\varphi}(\mathbf{x})\,, \tag{5}$$

where $\boldsymbol{\varphi}(\mathbf{x})$ represents a K-D vector composed of the basis functions $\{\varphi_k(\mathbf{x})\}$.

2.3. Experiment design considerations

In the traditional remote sensing approach to image formation [3], the matched filter $S^+ P_{U(M)} u_{(M)}(\mathbf{y}) = \hat{e}_{(K)}$ is first applied to the data $u_{(M)}(\mathbf{y})$ to form the estimate $\hat{e}_{(K)}(\mathbf{x})$ of the complex scattering function $e_{(K)}(\mathbf{x})$ and the resulting image is formed as the averaged squared modulus of such the estimates, i.e. $\hat{B}_{(K)}(\mathbf{x})= \mathrm{aver}\{|\,\hat{e}_{(K)}^{(j)}(\mathbf{x})|^2\}$. In that case, the degenerate Signal Formation Operator (SFO) $S_{(M)} = P_{U(M)} S$ uniquely specifies the system ambiguity function (AF) [12].

2.4. MR-DR strategy

In the descriptive statistical formalism, the desired SSP vector $\hat{\mathbf{B}}$ is recognized to be a vector of the principal diagonal of anstimate of the correlation matrix $\mathbf{R_E}(\mathbf{B})$, i.e. $\hat{\mathbf{B}} = \{\hat{\mathbf{R}}_\mathbf{E}\}_{\mathrm{diag}}$. Thus one can seek to estimate $\hat{\mathbf{B}} = \{\hat{\mathbf{R}}_\mathbf{E}\}_{\mathrm{diag}}$ given the data correlation matrix $\mathbf{R_U}$ pre-estimated by some means [4],

$$\hat{\mathbf{R}}_\mathbf{U} = \mathbf{Y} = \underset{j\in J}{\mathrm{aver}}\,\{\mathbf{U}_{(j)}\mathbf{U}^+_{(j)}\}, \tag{6}$$

by determining the solution operator $\mathbf{F}$ such that

$$\hat{\mathbf{B}} = \{\hat{\mathbf{R}}_\mathbf{E}\}_{\mathrm{diag}} = \{\mathbf{FYF}^+\}_{\mathrm{diag}}\,. \tag{7}$$

To optimize the search of $\mathbf{F}$ we propose here the following MR-DR *descriptive regularization* strategy

$$\mathbf{F} \to \min_{\mathbf{F}}\{\mathfrak{R}(\mathbf{F})\},$$
$$\mathfrak{R}(\mathbf{F}) = \mathrm{trace}\{(\mathbf{FS} - \mathbf{I})\mathbf{A}(\mathbf{FS} - \mathbf{I})^+\} + \alpha\,\mathrm{trace}\{\mathbf{F}\mathbf{R_N}\mathbf{F}^+\} \tag{8}$$

that implies the minimization of a weighted sum of the systematic and fluctuation errors in the desired estimate $\hat{\mathbf{B}}$, where the selection (adjustment) of the regularization parameter α and the weight matrix $\mathbf{A}$ provides the additional degreees of freedom incorporating any descriptive properties of a solution if those are known a priori [5], [6].

2.5. General form of solution operator

Routinely solving the minimization problem (8) we obtain

$$\mathbf{F} = \mathbf{K}_{\mathbf{A},\alpha}\mathbf{S}^{+}\mathbf{R}_{\mathbf{N}}^{-1}, \tag{9}$$

where

$$\mathbf{K}_{\mathbf{A},\alpha} = (\mathbf{S}^{+}\mathbf{R}_{\mathbf{N}}^{-1}\mathbf{S} + \alpha\mathbf{A}^{-1})^{-1} \tag{10}$$

and the desired SSP estimate is given by

$$\hat{\mathbf{B}}_{MR-ED} = \{\mathbf{K}_{\mathbf{A},\alpha}\mathbf{S}^{+}\mathbf{R}_{\mathbf{N}}^{-1}\mathbf{Y}\,\mathbf{R}_{\mathbf{N}}^{-1}\mathbf{S}\mathbf{K}_{\mathbf{A},\alpha}\}_{\text{diag}} = \{\mathbf{K}_{\mathbf{A},\alpha}\operatorname*{aver}_{j\in J}\{\mathbf{Q}_{(j)}\mathbf{Q}^{+}_{(j)}\}\mathbf{K}_{\mathbf{A},\alpha}\}_{\text{diag}}, \tag{11}$$

where $\mathbf{Q}_{(j)} = \{\mathbf{S}^{+}\mathbf{R}_{\mathbf{N}}^{-1}\mathbf{U}_{(j)}\}$ is recognized to be an output of the matched spatial processing algorithm with noise whitening.

2.6. MR-DR-robustified algorithms

2.6.1. Robust spatial filtering (RSF)
Putting $\mathbf{A} = \mathbf{I}$ and $\alpha = N_0/B_0$, where B_0 is the prior average gray level of the SSP, the $\mathbf{F}$ can be reduced to the following Tikhonov-type robust spatial filter

$$\mathbf{F}_{RSF} = \mathbf{F}^{(1)} = (\mathbf{S}^{+}\mathbf{S} + (N_0/B_0)\mathbf{I})^{-1}\mathbf{S}^{+}. \tag{12}$$

2.6.2. Matched spatial filtering (MSF)
In the previous scenario for $\alpha >> ||\mathbf{S}^{+}\mathbf{S}||$, the $\mathbf{F}$ becomes

$$\mathbf{F}_{MSF} = \mathbf{F}^{(2)} \approx const \cdot \mathbf{S}^{+} \tag{13}$$

i.e. reduces to the conventional MSF operator.

2.6.3. Adaptive spatial filtering (ASF)
Consider now the case of an arbitrary zero-mean noise with correlation matrix $\mathbf{R}_{\mathbf{N}}$, equal importance of two error measures in (9), i.e. $\alpha = 1$, and the solution dependent weight matrix $\mathbf{A} = \hat{\mathbf{D}} = \text{diag}(\hat{\mathbf{B}})$. In this case, the MR-DR solution operator defines the adaptive spatial filter

$$\mathbf{F}_{ASF} = \mathbf{F}^{(3)} = \mathbf{H} = (\mathbf{S}^{+}\mathbf{R}_{\mathbf{N}}^{-1}\mathbf{S} + \hat{\mathbf{D}}^{-1})^{-1}\mathbf{S}^{+}\mathbf{R}_{\mathbf{N}}^{-1}. \tag{14}$$

III. SIMULATIONS AND CONCLUDING REMARKS

In the present study, we simulated conventional side-looking imaging radar (i.e. the array was synthesized by moving antenna) with the SFO factored along two axes in the image plane: the azimuth (horizontal axis) and the range (vertical axis). We considered a triangular shape of the imaging radar range ambiguity function of 5 pixels width, and a $\sin(x)/x$ shape of the side-looking radar antenna radiation pattern of 15 pixels width at 0.5 from the peak level. Simulation results are presented in Figures 1–3. The figure notes specify each particular employed imaging method. All scenes are presented in the same 512-by-512 pixel image format. The advantage of reconstructive imaging using the MR-DR-optimal ASF estimator (Fig. 3) and its robustified suboptimal RSF version (Fig. 2) over the case of conventional MSF technique (Fig. 1) is evident. The spatial resolution is substantially improved with both (RSF and ASF) techniques; the regions of interest and distributed scene boundaries are much better defined.

The presented study revealed also the way for deriving the suboptimal RSF technique with substantially decreased computational load. Being a structural simplification of the optimal ASF estimator, the RSF technique permits efficient non-adaptive numerical implementation in both iterative and concise direct computational forms. The proposed robust and adaptive nonlinear estimators contain also some design parameters viewed as the system-level degrees of freedom, which with an adequate selection can improve the performance of the corresponding techniques. The proposed methodology could be considered as an alternative approach to the existing ones that employ the descriptive regularization paradigm [1] - [4] as well as the MR method for SAR image enhancement recently developed in [8], [9].

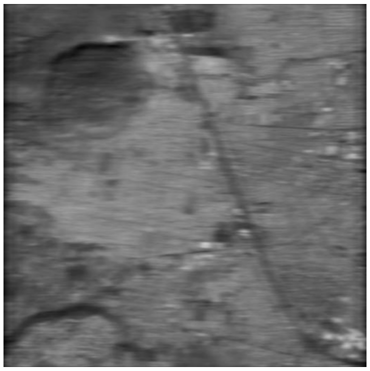

Fig. 1. Rough radar image formed using conventional MSF technique

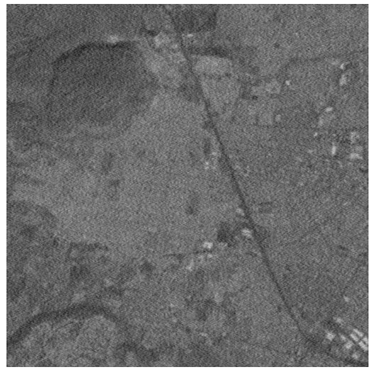

Fig. 2. Enhanced scene image formed applying the RSF method

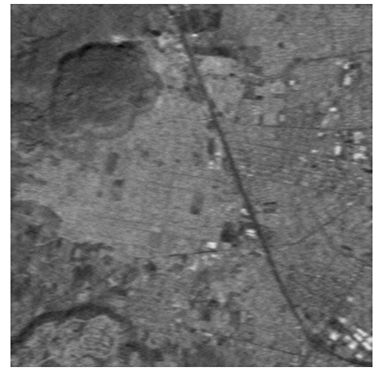

Fig. 3. Scene image reconstructed applying the ASF method

The provided simulation examples illustrate the overall performance improvements attainable with the proposed methods. The simulations were performed over a typical environmental scene borrowed from the real-world remote sensing imagery. The reconstructed CS maps are treated as sufficient statistical data required for performing the environmental resource management tasks.

IV. REFERENCES

[1] J. Munier, and G.L. Delisle, "Spatial analysis in passive listening using adaptive techniques", in *Proc. IEEE*, **75**, pp. 21-37, 1987.

[2] S.E. Falkovich, V.I. Ponomaryov and Y.V. Shkvarko, *Optimal Reception of Space-Time Signals in Channels with Scattering*, Moscow: Radio i Sviaz Press, 1989.

[3] A.K. Jain, *Fundamentals of Digital Image Processing,* N.J.: Englewood Cliffs, 1989.

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

[5] I. Chudinovich and C. Constanda, *Variational and Potential Methods in the Theory of Bending of Plates with Transverse Shear Deformation*, Boca Raton-London-New York-Washington DC: Chapman & Halls/CRC, 2002.

[6] 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.

[7] 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.

[8] J. Capon, "High-resolution frequency-wavenumber spectrum analysis", in *Proc. IEEE ,* 1969, vol. 57, pp. 1408-1410.

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

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

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

[12] Y. V. Shkvarko and I. E. Villalon-Turrubiates, "Intelligent Processing of Remote Sensing Imagery for Decision Support in Environmental Resource Management: A Neural Computing Paradigm", *16th Annual Information Resources Management Asociation (IRMA) International Conference: Managing Modern Org. with Information Technologies*, pp. 1060-1062, 2005.