Adaptive Algorithm-Based Fused Bayesian Maximum Entropy-Variational Analysis Methods for Enhanced Radar Imaging

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Abstract. In this paper we address an adaptive computational algorithm to improve the Bayesian maximum entropy–variational analysis (BMEVA) performance for high resolution radar imaging and denoising. Furthermore, the variational analysis (VA) approach is aggregated by imposing the metrics structures in the corresponding signal spaces. Then, the formalism for combining the Bayesian maximum entropy strategy with the VA paradigm is presented. Finally, the image enhancement and denoising benefits produced by the proposed Adaptive Bayesian maximum entropy–variational analysis (ABMEVA) method are showed via simulations with real-world radar scene

Keywords: Bayesian Maximum Entropy, data fusion, adaptive algorithm, variational analysis.

1 Introduction

Recently, the Bayesian maximum entropy (BME) method was developed in [2], where the Bayesian estimation method for high resolution radar image formation [1], [13], [15] employs the maximum entropy (ME) information theoretical-based windowing of the resulting images. Moreover, the alternative approach to radar image enhancement and denoising was proposed in [3] where the variational analysis (VA) paradigm was applied in [4], [14] to control the image gradient flow over the sensing scene using the difference-form approximations of the partial differential equations (PDE) to formalize different image processing problems including image segmentation, enhancement and denoising [3], [7], [11]. This strategy is adapted for a particular remote sensing system model and robust a priori information about the noise's statistics and the desired image. The BME is associated in [6], [7],[10] with the spatial spectrum pattern (SSP) of the wavefield backscattered from the probing surface. As the SSP represents the power distribution in the RS environment, the power non-negativity constraint is incorporated implicitly in the BME strategy but that do not

incorporate specific VA geometrical properties of the image, e.g. its gradient flow over the scene/frame [14]. However, the so called data fusion [12] strategy is a useful way to aggregate the BME statistical approach to optimize the VA-based radar image enhancement using a priori information [8]. The fused BMEVA approach [8] is presented and developed into a robust formalism without an efficient computational performance [10]. However, in recent years, several efforts have been directed toward the high performance computing because the computational load and implementation represents critical problem [16]. Based on the previous thing, the following problem arises: how to include the aggregate the BMEVA method for performing the combined statistical-descriptive enhancement of the radar images based on adaptive algorithm?

2 Inverse Problem Statement

Based on [1], [2], we define the model of the observation wavefield u by specifying the stochastic equation of observation of an operator form $u = Se + n$; $e \in \mathbf{E}$; $u, n \in \mathbf{U}$; $S: \mathbf{E} \rightarrow \mathbf{U}$, in Hilbert signal spaces $\mathbf{E}$ and $\mathbf{U}$ with the metrics structures induced by the inner products, $[u_1, u_2]_{\mathbf{U}}$ and $[e_1, e_2]_{\mathbf{E}}$, respectively, where the Gaussian zero-mean random fields e , n , and u correspond to the initial scattered field, noise and observation wavefield, respectively. Now, recalling the experiment design (ED) theory-based projection formalism [2], one can proceed from the operator form equation of observation to its finite-dimensional vector form,

$$\mathbf{U} = \mathbf{S} \mathbf{E} + \mathbf{N}. \quad (1)$$

In which $\mathbf{E}$, $\mathbf{N}$, and $\mathbf{U}$ represent the zero-mean Gaussian vectors with the correlation matrices $\mathbf{R}_E = \mathbf{R}_E(\mathbf{B}) = \text{diag}\{\mathbf{B}\}$, $\mathbf{R}_N$, and $\mathbf{R}_U = \mathbf{S} \mathbf{R}_E \mathbf{S}^+ + \mathbf{R}_N$, respectively, where $\text{diag}\{\mathbf{B}\}$ is a diagonal K -by- K matrix with elements $B_k = \langle E_k E_k^* \rangle$ and $\langle \cdot \rangle$ defines the statistical averaging operator. Vector $\mathbf{B}$ is referred to as the spatial spectrum pattern (SSP) vector that represents the average brightness image of the remotely sensed scene, and matrix $\mathbf{S}$ defines the signal formation operator (SFO).

3 Bayesian Maximum Entropy and Variational Analysis

3.1 BME Analysis

The processing of the observation data $\mathbf{U}$ is used to obtain an unique and stable estimate $\hat{\mathbf{B}}$. However, because of the ill-posed nature of such the image reconstruction problem [2] the SFO, in general, is ill-conditioned or even singular. The ME principle [2], [5] provides the well-grounded way to alleviate the problem ill-posedness. Based on the ME paradigm, the whole image is viewed as a composition of a great amount of elementary discrete (speckles or pixels) with the elementary “pixel brightness”. Following the ME approach in [9], the a priori pdf $p(\mathbf{B})$ of the desired image is defined via maximization the entropy of the image probability that satisfies also the constraints imposed by the prior knowledge [2]. The vector $\mathbf{B}$ is viewed as an element

of the K -D vector space $B_{(K)} \ni \mathbf{B}$ with the squared norm imposed by the inner product $\|\mathbf{B}\|_{B(K)}^2 = [\mathbf{B}, \mathbf{M}\mathbf{B}]$, where $\mathbf{M}$ is the positive definite metrics inducing matrix [2]. In addition, the physical factors of the experiment can be generalized imposing the physically obvious constraint bounding the average squared norm of the SSP [2],

$$\int_{B_C} [\mathbf{B}, \mathbf{M}\mathbf{B}] p(\mathbf{B}) d\mathbf{B} \leq c_0 . \quad (2)$$

Thus, the a priori pdf $p(\mathbf{B})$ is to be found as a solution to the Lagrange maximization problem, with the Lagrange multipliers α , and λ . Such a problem is specified as follows

$$\begin{aligned} -\int_{B_C} \ln p(\mathbf{B}) p(\mathbf{B}) d\mathbf{B} - \alpha (\int_{B_C} [\mathbf{B}, \mathbf{M}\mathbf{B}] p(\mathbf{B}) d\mathbf{B} - c_0) \\ - \lambda (\int_{B_C} p(\mathbf{B}) d\mathbf{B} - 1) \rightarrow \max_{p(\mathbf{B})} , \end{aligned} \quad (3)$$

for $\mathbf{B} \in B_C$, and $p(\mathbf{B}) = 0$ otherwise. The solution to (3) was derived in [2] that yields the Gibbs-type a priori pdf

$$p(\mathbf{B} | \alpha) = \exp\{-\ln \sum (\alpha) - \alpha [\mathbf{B}, \mathbf{M}\mathbf{B}]\} , \quad (4)$$

where $\sum(\alpha)$ represents the so-called Boltzmann statistical sum [2]. The log-likelihood [2] of the vector $\mathbf{B}$ is defined as

$$\begin{aligned} \Lambda(\mathbf{B} | \mathbf{U}) = \ln p(\mathbf{B} | \mathbf{U}) = -\ln \det\{\mathbf{S}\mathbf{D}(\mathbf{B})\mathbf{S}^+ + \mathbf{R}_N\} \\ - [\mathbf{U}, (\mathbf{S}\mathbf{D}(\mathbf{B})\mathbf{S}^+ + \mathbf{R}_N)^{-1} \mathbf{U}] , \end{aligned} \quad (5)$$

and BME strategy for image reconstruction (estimation of the SSP vector $\mathbf{B}$) is stated as follows,

$$\hat{\mathbf{B}} = \arg \min_{\mathbf{B}, \alpha} \{-\Lambda(\mathbf{B} | \mathbf{U}) - \ln p(\mathbf{B} | \alpha)\} . \quad (6)$$

The BME estimate of the SSP is a solution to the problem (6) and is given by the nonlinear equation [2]

$$\hat{\mathbf{B}} = \mathbf{W}(\hat{\mathbf{B}}) [\mathbf{V}(\hat{\mathbf{B}}) - \mathbf{Z}(\hat{\mathbf{B}})] . \quad (7)$$

Here, $\mathbf{V}(\hat{\mathbf{B}}) = \{\mathbf{F}(\hat{\mathbf{B}}) \mathbf{U} \mathbf{U}^+ \mathbf{F}^+(\hat{\mathbf{B}})\}_{\text{diag}}$ is a vector that has the statistical meaning of a sufficient statistics (SS) for the SSP estimator, operator $\mathbf{F}(\hat{\mathbf{B}}) = \mathbf{D}(\hat{\mathbf{B}})(\mathbf{I} + \mathbf{S}^+ \mathbf{R}^{-1} \mathbf{N} \mathbf{S} \mathbf{D}(\hat{\mathbf{B}}))^{-1} \mathbf{S}^+ \mathbf{R}^{-1} \mathbf{N}$ is referred to as the SS formation operator, the vector $\mathbf{Z}(\hat{\mathbf{B}}) = \{\mathbf{F}(\hat{\mathbf{B}}) \mathbf{R}_N \mathbf{F}^+(\hat{\mathbf{B}})\}_{\text{diag}}$ is the shift or bias vector, and $\mathbf{W}(\hat{\mathbf{B}}) = (\mathbf{T}(\hat{\mathbf{B}}) + 2 \hat{\alpha} \mathbf{D}^2(\hat{\mathbf{B}}) \mathbf{M})^{-1}$ has the statistical meaning of a solution dependent (i.e., adaptive) window operator with the stabilizer $\mathbf{T}(\hat{\mathbf{B}}) = \text{diag}\{\{\mathbf{S}^+ \mathbf{F}^+(\hat{\mathbf{B}}) \mathbf{F}(\hat{\mathbf{B}}) \mathbf{S}\}_{\text{diag}}\}$. Adaptation is to be performed by both the current SSP estimate, $\hat{\mathbf{B}}$, and the estimate of the normalizing constant $\hat{\alpha}$ determined from a solution of the equation $-\partial/\partial\alpha (\ln \sum(\alpha)) = [\hat{\mathbf{B}}, \mathbf{M}\hat{\mathbf{B}}]$.

3.2 Variational Analysis

Based on the anisotropic diffusion in [4], the idea is to evolve from an original image $B(x, y)$, defined in a convex domain Ω , to a family of increasingly smooth images $B(x, y, t)$ derived from the solution. The diffusion algorithm reduces the noise from an image by modifying the image via a partial differential equation (PDE). Now, looking for a statistical interpretation of the Perona-Malik [4] anisotropic diffusion equation it is possible to make the robustification of the VA-based image model. The generalized robustified VA energy function is defined as [3]

$$VA(\mathbf{B}) = \int_{\Omega} \rho(\|\nabla \mathbf{B}\|) d\Omega \quad . \quad (8)$$

over the image domain Ω , where

$$\rho(x) = \int g(x)x dx = \sigma^2 \log \left[1 + \frac{1}{2} \left(x^2 / \sigma^2 \right) \right] \quad . \quad (9)$$

is the Lorentz function, and

$$g(x) = \rho'(x)/x \quad . \quad (10)$$

is the auxiliary function that defines the relation between the different reconstructed images after applying the robust VA estimation method [4].

The VA approach assumes the minimization of (8) via gradient descent flow using the calculus of variations as follows,

$$VA(\hat{\mathbf{B}}) = \arg \min_{\mathbf{B}} \int_{\Omega} \rho(\|\nabla \mathbf{B}\|) d\Omega \quad . \quad (11)$$

In such the VA approach, the critical issue is the choice of the variational functional. Recall that in this study we follow the Lagrangian model given by (8).

4 Fused BMEVA Method

Now, the fused BMEVA method for image reconstruction presented in [8], [10] combine the VA and BME approaches and the formalism used the following strategies

$$\hat{\mathbf{B}} = \arg \min_{\mathbf{B}, \alpha} \{ -\Lambda(\mathbf{B} | \mathbf{U}) - \ln p(\mathbf{B} | \alpha) \} \rightarrow \text{Optimal BME} \quad , \quad (12)$$

$$VA(\hat{\mathbf{B}}) = \arg \min_{\mathbf{B}} \int_{\Omega} \rho(\|\nabla \mathbf{B}\|) d\Omega \rightarrow \text{Optimal VA} \quad . \quad (13)$$

It is important to understand that both the BME and VA approaches look for an enhanced reconstruction with edge preservation. Henceforth, the proposed fused BMEVA reconstruction strategy assumes the solution to the variational problem

$$\hat{\mathbf{B}}_{BMEVA} = \arg \min_{\mathbf{B}, \alpha} \{ -\Lambda(\mathbf{B} | \mathbf{U}) - \ln p(\mathbf{B} | \alpha) + \int_{\Omega} \rho(\|\nabla \mathbf{B}\|) d\Omega \} \quad (14)$$

The logarithm series expression is a viable mathematical tool to obtain the numerical approximation from the energy function by series. Recalling [8], the conventional gradient method [4] is used to solve (14), but in this case $n=3$ to minimize the third term on the second member in (14), as following,

$$\sigma^2 \log \left[1 + \left(\frac{\|\nabla \mathbf{B}\|}{\sigma\sqrt{2}} \right)^2 \right] = \sigma^2 \sum_{n=1}^2 \frac{(-1)^{n+1} \left(\frac{\|\nabla \mathbf{B}\|}{\sigma\sqrt{2}} \right)^{2n}}{n} = \mathbf{B}^+ \mathbf{Q} \mathbf{B} , \quad (15)$$

where

$$\mathbf{Q} = (1/2)\mathbf{L} + \tau_1 \mathbf{L}\mathbf{L} + \tau_2 \mathbf{L}\mathbf{L}\mathbf{L} \quad (16)$$

is the composed weighting matrix and the regularization parameters: $\tau_1 = -1/8\sigma^2$ and $\tau_2 = 1/24\sigma^4$, respectively. The matrix $\mathbf{L}$ represents the numerical approximation of the Laplacian operator [7].

Now, the solution to problem (14) can be expressed in a form of the nonlinear equation

$$F(\mathbf{B}, \alpha) = \ln \det \{ \mathbf{S} \mathbf{D}(\mathbf{B}) \mathbf{S}^+ + \mathbf{R}_N \} + [\mathbf{U}, (\mathbf{S} \mathbf{D}(\mathbf{B}) \mathbf{S}^+ + \mathbf{R}_N)^{-1} \mathbf{U}] \\ + \ln \sum (\alpha) + \alpha [\mathbf{B}, \mathbf{M} \mathbf{B}] + [\mathbf{B}, \mathbf{Q} \mathbf{B}] . \quad (17)$$

$$\partial F(\mathbf{B}, \alpha) / \partial \mathbf{B} = 0 \quad \text{and} \quad \partial F(\mathbf{B}, \alpha) / \partial \alpha = 0 . \quad (18)$$

As it was detailed in [2], because of the nonlinearity, no unique regular method for solving (18) exists; however, one can represent the solution in a form convenient for the further analysis. To proceed in this direction, we follow the methodology proposed in [2] which yields the equation

$$\mathbf{T} \mathbf{B} + \mathbf{Z} - \mathbf{V} + 2\alpha \mathbf{D}^2 \mathbf{M} \mathbf{B} + 2\mathbf{Q} \mathbf{B} = 0 . \quad (19)$$

Grouping the terms and replacing $\alpha \rightarrow \hat{\alpha}$ from (18) we obtain

$$\mathbf{T} \mathbf{B} + \mathbf{Z} - \mathbf{V} + 2\hat{\alpha} \mathbf{D}^2 \mathbf{M} \mathbf{B} + 2\mathbf{Q} \mathbf{B} = 0 . \quad (20)$$

Finally, solving (20) with respect to $\mathbf{B}$ and exposing the dependence of $\mathbf{T}(\mathbf{B})$, $\mathbf{D}(\mathbf{B})$, $\mathbf{V}(\mathbf{B})$, and $\mathbf{Z}(\mathbf{B})$ on the solution we obtain

$$\hat{\mathbf{B}} = \mathbf{W}(\hat{\mathbf{B}}) [\mathbf{V}(\hat{\mathbf{B}}) - \mathbf{Z}(\hat{\mathbf{B}})] , \quad (21)$$

where

$$\mathbf{W}(\hat{\mathbf{B}}) = (\mathbf{T}(\hat{\mathbf{B}}) + 2\hat{\alpha} \mathbf{D}^2(\hat{\mathbf{B}}) \mathbf{M} + 2\mathbf{Q})^{-1} . \quad (22)$$

represents the adaptive spatial window operator.

5 The Adaptive Computational Algorithm

The derived BMEVA estimator (21) can be converted into an efficient iterative algorithm using the LMS iteration method [11]. Pursuing such the approach [11], we refer to the SSP estimate on the right-hand side in (21) as the current estimate $\hat{\mathbf{B}}^{(t)}$ at the t th iteration step, and associate the entire right-hand side of (21) with the rule for forming the estimate $\hat{\mathbf{B}}^{(t+1)}$ for the next iteration step ($t+1$) that yields

$$\hat{\mathbf{B}}^{(t+1)} = \hat{\mathbf{B}}^{(t)} + \gamma [\hat{\mathbf{B}}^{(t+1)} - \hat{\mathbf{B}}^{(t)}]. \quad (23)$$

Due to the performed regularized windowing (20), the iterative algorithm (23) converges in a polynomial time [8] regardless of the choice of the balance factor γ within the prescribed normalization interval, $0 \leq \gamma \leq 1$.

6 Simulations and Concluding Remarks

Now, the imagery results obtained by the new adaptive computational algorithm are enough qualitative evidence to discuss the ABMEVA computational efficiency. Figure 1 shows the original 256-by-256 simulated scene $\mathbf{B}$ and the computed results using the Match Spatial Filter (MSF), VA, BME, BMEVA and the ABMEVA algorithms for the $\exp(-bx^2)$ of the point spread functions (PSF), i.e. system 1: Gaussian “Bell”-type PSF. Moreover, the Figure 2 shows the results of the image enhancement

a. Original super-high resolution scene

b. Image formed with the MSF method

c. Image post-processed with the VA method

d. SSP reconstructed with the BMEVA method

e. SSP reconstructed with the ABMEVA ($\gamma=0.6$)

f. SSP reconstructed with the ABMEVA method ($\gamma=0.9$)

Fig. 1. Simulation results for $\mathbf{B}$ scene (first system model)

a. Original super-high resolution scene

b. Image formed with the MSF method

c. Image post-processed with the VA method

d. SSP reconstructed with the BMEVA method

e. SSP reconstructed with the BMEVA ($\gamma=0.25$)

f. SSP reconstructed with the ABMEVA method ($\gamma=0.7$)

Fig. 2. Simulation results for **B** scene (second system model)

a. Original super-high resolution scene

b. Image formed with the MSF method

c. Image post-processed with the VA method

d. SSP reconstructed with the BMEVA method

e. SSP reconstructed with the ABMEVA ($\gamma=0.6$)

f. SSP reconstructed with the ABMEVA method ($\gamma=0.9$)

Fig. 3. Simulation results for **B'** scene (first system model)

Fig. 4. Simulation results for **B'** scene (second system model)

Table 1. Scene **B**-based results for two different simulated SAR systems

SNR [dB]	IOSNR [dB] System 1					IOSNR [dB] System 2			
	Reconstruction Method				VA	Reconstruction Method			VA
	μ	VA	BMEVA	ABMEVA ($\gamma=0.6$)	ABMEVA ($\gamma=0.9$)	BMEVA	ABMEVA ($\gamma=0.25$)	ABMEVA ($\gamma=0.7$)	
10		0.635	2.120	8.301	9.711	1.335	3.025	11.926	13.575
15		0.638	2.625	8.322	9.753	1.351	3.128	11.941	13.581
20		0.638	3.142	8.354	9.773	1.356	4.335	11.978	13.590
25		0.640	4.430	8.369	9.781	1.358	5.498	11.982	13.603
30		0.642	4.732	8.375	9.800	1.360	6.133	11.993	13.615

using the $\sin(ax)/ax$, i.e. system 2: sinc-type PSF. On the other hand, the Table 1 manifests the strong quantitative analysis to valid the computational performance based on input-output signal-noise ratio (IOSNR) metric [2]. Following this way, the Table 2, Figure 3, and Figure 4 show the results based on simulated scene **B'** to match the quantitative and qualitative analysis.

In summary, we may conclude that the proposed ABMEVA method provides the substantially improved image enhancement and reconstruction achieved due to performing the adaptive windowing in the flat regions with preserving the edge features. The new approach presents a new computational technique to improve the BMEVA

Table 2. Scene **B'**-based results for two different simulated SAR systems

SNR [dB]	IOSNR [dB] System 1				IOSNR [dB] System 2			
	Reconstruction Method				Reconstruction Method			
	μ	VA	BMEVA	ABMEVA ($\gamma=0.6$)	ABMEVA ($\gamma=0.9$)	VA	BMEVA	ABMEVA ($\gamma=0.25$)
10	1.020	12.454	7.393	10.268	0.724	3.948	6.293	10.382
15	1.132	12.625	7.444	10.465	0.751	4.339	6.445	10.662
20	1.129	12.957	7.834	10.628	0.779	4.613	6.608	10.873
25	1.166	13.032	8.102	10.831	0.822	4.903	6.868	11.241
30	1.171	13.073	8.123	10.870	0.837	5.249	7.017	11.388

performance. A key distinguish feature of the ABMEVA method is that the problem of image enhancement and denoising is solved in the framework of Bayesian estimation theory that incorporates the VA considerations through the fused reconstruction strategy. Finally, the proposed ABMEVA manifest a robust performance for different formation systems-based radar imaging.

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