NEURAL NETWORK COMPUTATIONAL TECHNIQUE FOR HIGH-RESOLUTION REMOTE SENSING IMAGE RECONSTRUCTION WITH SYSTEM FUSION

Yuriy V. Shkvarko, *Senior Member, IEEE*, **Jose L. Leyva-Montiel,** *Member, IEEE*, and **Ivan E. Villalon-Turrubiates**, *Member, IEEE*

CINVESTAV del IPN, Unidad Guadalajara,
Pról. Av. López Mateos Sur 590, Apartado Postal 31-438, C.P. 45090, Guadalajara Jal., MEXICO
Tel: (+5233) 31345570 + 2041, Fax: (+5233) 31345579, E-mail: shkvarko@gdl.cinvestav.mx

ABSTRACT

We address a new approach to the problem of improvement of the quality of scene images obtained with several sensing systems as required for remote sensing imagery, in which case we propose to exploit the idea of robust regularization aggregated with the neural network (NN) based computational implementation of the multi-sensor fusion tasks. Such a specific aggregated robust regularization problem is stated and solved to reach the aims of system fusion with a proper control of the NN's design parameters (synaptic weights and bias inputs viewed as corresponding system-level and model-level degrees of freedom) which influence the overall reconstruction performances.

Keywords: Signal processing, image reconstruction, system fusion, regularization, neural networks.

1. INTRODUCTION

In this paper, the problem of reconstructive imaging with system fusion is treated as required for multisensor/ multisource remote sensing (RS) imagery [1], [2]. Usually, an active or passive RS imaging system (radar, sonar, infrared, seismic, etc.) performs specific space-time processing of the random electromagnetic or acoustic field impinging on the system sensor or array of sensors with the purpose of obtaining an estimate of the power pattern of wavefield sources distributed in the environment, the so-called spatial spectrum pattern (SSP) [7], [10] referred to as an image of the environment produced by a system [1], [2]. It is clear that in the case of multiple RS systems that may employ different imaging methods (linear, nonlinear, adaptive and robustified) with different system-level constraints (e.g. calibration data, noise and signal statistical model uncertainties), there are particular properties of RS images that demand reconstruction techniques different from those recently proposed for conventional optical and non fused RS imagery [3], [4], [5], [6], [7].

The key distinguishing features of the approach considered in the present study are as follows:

(i) the problem of image reconstruction with system fusion is stated and treated as an aggregated *ill-conditioned inverse problem* of reconstruction of the desired image from the degraded images provided by different sensing systems with model uncertainties about the signal and noise statistics and uncertain system calibration data;

(ii) we propose to approach this problem by exploitation of nontrivial information on the performances of the corresponding systems to be fused combined with prior realistic knowledge about the properties of the scene contained in the maximum entropy a priori image model and robust incorporation of some system-level constrains (e.g. in the case of uncertainty, only the robust prior information on the bounded total output image variance and overall resolution-to-noise balance is to be incorporated);

(iii) to accomplish the system fusion computationally, we investigated the fine structure of the Li's multistate maximum entropy neural network (MENN) [8], and propose its robust modification to enable the network to solve the aggregate fusion-reconstruction problem. Such an intelligent aggregation (not simple compilation) of the robust system fusion approach with the NN computational paradigm distinguishes the present study from the previously proposed image reconstruction and sensor fusion techniques reported in [4], [5], [8], [9], [10].

2. PROBLEM PHENOMENOLOGY

According to the mathematical statement [5], [8] to perform the image enhancement via NN-based signal processing of the RS data employing the system/method fusion one have to solve the maximum entropy (ME) conditional optimization problem

$$\hat{\mathbf{v}} = \underset{\mathbf{v}}{\operatorname{argmin}}\, E(\mathbf{v}\,|\boldsymbol{\lambda}) \qquad (1)$$

of minimizing the cost (energy) function

$$E(\mathbf{v}|\boldsymbol{\lambda}) = -\ H(\mathbf{v}) + (1/2)\sum_{m=1}^{M} \lambda_m J_m(\mathbf{v}) + (1/2)\lambda_{M+1}J_{M+1}(\mathbf{v}) \qquad (2)$$

with respect to the desired K-D image vector $\mathbf{v}$ for the assigned (or adjusted) values of the regularization parameters $\boldsymbol{\lambda}$. The proper selection of $\boldsymbol{\lambda}$ is associated with parametrical optimization of the fusion process. In (2), $H(\mathbf{v}) = -\sum_{k=1}^{K} v_k \ln v_k$ is the image entropy [4] computed for all image pixels v_k,; $k = 1, \ldots, K$; $J_m(\mathbf{v}) = ||\mathbf{u}^{(m)} - \mathbf{F}^{(m)}\mathbf{v}||^2$ represent the partial error functions for corresponding M RS systems, $m = 1, \ldots, M$; and $J_{M+1}(\mathbf{v})$ represents the conventional Tikhonov's stabilizer [11]. The data acquisition model is defined, as in [8], by the set of equations, $\mathbf{u}^{(m)} = \mathbf{F}^{(m)}\,\mathbf{v} + \mathbf{n}^{(m)}$; $m = 1, \ldots, M$, where $\mathbf{F}^{(m)}$ represents the corresponding mth system degradation operator usually referred to as the imaging system point spread functions (PSF) [4] and $\mathbf{n}^{(m)}$ represents the noise in the actually acquired corresponding mth image, respectively. In our previous study [8], the aggregate regularization-based method for proper selection of $\boldsymbol{\lambda}$ was proposed, which guarantees the optimal resolution-to-noise balance when the optimal enhancement-fusion problem (1) is solved. It is important to note that the ME solution $\hat{\mathbf{v}}$ exists and is guaranteed to be unique for a given $\boldsymbol{\lambda}$ because the surfaces of all functions that compose E($\mathbf{v}$|$\boldsymbol{\lambda}$) given by (2) are convex. Furthermore, the entropy is defined only for the positive values, hence, the ME solution is guaranteed to be positive. But one can deduce from an analysis of problem (1), (2) that due to the non-linearity of the objective function the solution of the parametrically controlled enhancement-fusion problem (1) will require extremely complex computations and will result in the technically intractable fusion scheme if solve this problem employing the standard direct minimization techniques [3], [12]. For this reason, we propose here to apply the NN-based computing paradigm for solving the aggregate enhancement-fusion problem (1). Because of the specific computational capabilities the framework of such the intelligent NNs is very convenient for fusion design [4], [5], [8].

3. MENN FOR MULTISENSOR IMAGE FUSION

The dynamic NN which we propose to solve the problem (1) is a further modification of the Li´s maximum entropy NN (MENN) [5] originally modified in [8] to enable that to perform the system fusion tasks. Changing the rule for computing the states of the MENN performs the modification. Instead of the empiric calibration-based adjustment of the parameters $\boldsymbol{\lambda}$, those are now adaptively controlled using the aggregation method developed in [8].

Consider the multistate Hopfield-type (i.e. dynamic) NN [3], [4] with the K-D state vector $\mathbf{x}$ and K-D output vector $\mathbf{z} = \operatorname{sgn}(\mathbf{Wx} + \boldsymbol{\theta})$, where $\mathbf{W}$ and $\boldsymbol{\theta}$ are the matrix of synaptic weights and the vector of bias inputs of the NN, respectively. The energy function of the NN is expressed as [8]

$$E = -\,(1/2)\sum_{k=1}^{K}\sum_{m=1}^{K} W_{km}x_k x_m - \sum_{k=1}^{K}\theta_k x_k\ . \qquad (3)$$

The idea of solving the image enhancement problem (1) with system fusion using the dynamic NN is based on the following proposition [8]: *if the energy function of the NN represents the function of a mathematical minimization problem over a parameter space, then the state of the NN would represent the parameters and the stationary point of the network would represent a local minimum of the original minimization problem*. Hence, utilizing the concept of the dynamic NN, we may translate our image reconstruction/enhancement inverse problem with RS system fusion to the corresponding problem of minimization of the energy function of a modified MENN. Therefore, we define now the parameters of the modified MENN in such a fashion that to aggregate the corresponding parameters of the imaging RS systems to be fused,

$$W_{ki} = -\sum_{m=1}^{M}\Big[\,\lambda_m \sum_{j=1}^{K} F_{jk}^{(\mathrm{m})} F_{ji}^{(\mathrm{m})}\,\Big] - \lambda_{M+1}P_{ki}\ ;$$

$$\theta_k = -\ln v_k + \sum_{m=1}^{M}\Big[\ \lambda_m \sum_{j=1}^{K} F_{jk}^{(\mathrm{m})}\ \mathrm{u}_j^{(\mathrm{m})}\ \Big] \qquad (4)$$

for all $k, i = 1, \ldots, K$.

To find a minimum of the energy function (3), the states of the network should be updated from iteration to iteration $\mathbf{x}^{\prime\prime}=\mathbf{x}^{\prime}+\Delta\mathbf{x}$ using some properly designed update rule $\Re(\mathbf{z})$ where the superscripts $'$ and $''$ correspond to the state values before and after network state updating (at each iteration), respectively, and $\Delta\mathbf{x}$ defines a change in the MENN´s state vector. In this study, we employ the rule developed in our previous paper [8] that guarantees the nonpositive values of the energy changes ΔE, i.e.

$$\Delta x_k = \Re(z_k) = \begin{cases} 0 & \text{if} \quad z_k = 0\,, \\ \Delta & \text{if} \quad z_k > 0\,, \\ -\Delta & \text{if} \quad z_k < 0\,, \end{cases} \qquad (5)$$

where Δ is the preassigned step-size parameter [8].

While implementing the MENN algorithm, the values of the regularization parameters in (4) may be chosen empirically [5] or controlled applying the aggregation schemes proposed in our previous study [8]. Hence, via integrating the aggregation method [8] with the NN given by (4), (5), we propose the following scheme for adaptive adjustment of the MENN´s weighting parameters in (4) as follows,

$$\hat{\lambda}_m = \hat{\omega}^{-1}\hat{\pi}_m \;, \qquad \hat{\pi}_m = r_m \Big/ \sum_{i=1}^{M} r_i \;, \qquad (6)$$

where r_{m} = trace $\{(\mathbf{F}^{(m)})^{-2}\}$ is the corresponding system's resolution factor, and $\hat{\omega}$ is to be found as a solution to the noise-to-resolution balance equation (equation (13) from [8]). Thus, the idea of computational implementation of the proposed aggregated fusion method using a NN is based on the modification of the Li´s MENN algorithm [8] *without* complicating the NN's computational structure *independent* on a number of systems to be fused. To accomplish this we redefine the NN's operation parameters $\mathbf{W}$, $\boldsymbol{\theta}$ in such the fashion (4) that the new MENN algorithm integrates the model parameters of all M systems that enables the network to perform the fusion. Note that via integrating the presented above MENN algorithm with two optimization methods for system-oriented or problem-oriented data aggregation [8], other different modifications of the developed here MENN-based system fusion technique can also be proposed.

3. NUMERICAL SIMULATIONS

The computer simulations of the proposed here method were carried out in two dimensions for the case of two RS imaging systems, i.e. M = 2. We tested two different models of the symmetric system point spread functions (PSFs): PSF_1 of a a Gaussian "bell" shape of 20 pixels width at half maximum, and PSF_2 of a squared "sinc" shape of 10 pixels width at half maximum, in the horizontal direction of the 2-D scene. The original image was of 512-by-512 pixel format in size. The chi-squared random additive noise was aggregated to the images to emphasize the performance of the fusion method. Its variance was 5% of the image average gray level for the first system model and 10% for the second system model, respectively. The simulation results are shown in Figures 1 - 5. Also, we tested the results of image enhancement without system fusion which employed the inverse filtering techniques [2], [11] but all those provided unsatisfactory poor quality of restoration even for the low noise levels. Some of the results of simulations carried out in one and two dimensions without optimal data aggregation were also reported in our previous work [8].

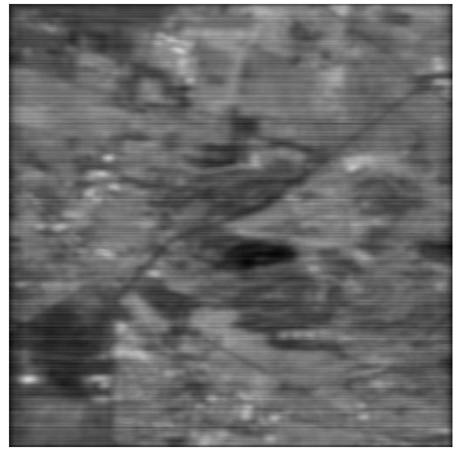

Fig. 1. Initial radar image provided with the 1st system (SAR with the fractionally synthesized aperture)

Fig. 2. Initial radar image provided with the 2nd system (SAR with the fractionally synthesized aperture)

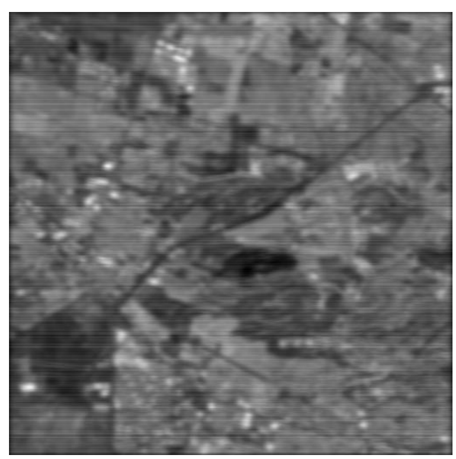

Fig. 3. MENN-reconstructed image of the 1st system (without system fusion)

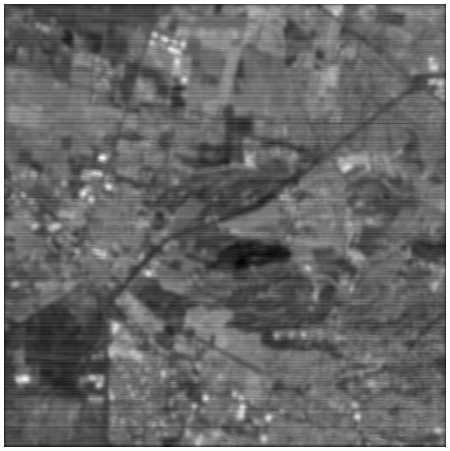

Fig. 4. MENN-reconstructed image of the 2nd system (without system fusion)

Fig. 5. Fused image reconstructed from the images of Fig.1 and Fig. 2; the fusion was performed applying the developed MENN technique

4. CONCLUDING REMARKS

The aggregated multisensor/multisource digital imaging problem was stated and solved numerically via NN computing to reach the aims of system fusion with control of the system-level and model-level design parameters (degrees of freedom) which influence the overall reconstruction performances as required for the multisensor/multisource remote sensing imagery, although the developed methodology could be addressed also for other fields.

The principal result of the undertaken research can be summarized as follows: due to the unified architecture and computational parallelism, the developed MENN is able to perform the system fusion tasks without cardinal complication of its structure independent on the number of systems to be fused. Only the proper readjustment of the MENN's computational parameters (i.e. synaptic weights and bias inputs) must be accomplished in each particular case to enable the MENN to perform the developed fusion method.

As a final point of study, we presented some simulation examples indicative of the enhancement of the overall performances of the aggregated image reconstruction with sensor fusion achieved with the developed MENN method in its application to reconstructive imaging with the real-world RS data provide by two SAR imaging systems.

5. REFERENCES

[1] 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.

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

[3] J.B. Abbis, B.J. Brames and M.A. Fiddy, "Superresolution algorithms for a modified Hopfield neural network", *IEEE Trans. Signal Proccesing*, vol. 39, pp. 1516-1523, 1991.

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

[5] J.K. Paik and A.K. Katsaggelos, "Image restoration using a modified Hopfield network", *IEEE Trans. Image Processing*, vol. 1, pp. 49-63, 1992.

[6] B. Kosko, *Neural Networks for Signal Processing*, New York: Prentice Hall, 1992.

[7] S. Haykin, *Neural Networks: A Comprehensive Foundation*, New York: Macmillan, 1994.

[8] Y. V. Shkvarko, Y. S. Shmaliy, R. Jaime-Rivas and M. Torres-Cisneros, "System fusion in passive sensing using a modified Hopfield network", *Journal of the Franklin Institute*, **338**, pp. 405–427, 2000.

[9] Y. V. Shkvarko, "Estimation of wavefield power distribution in the remotely sensed environment: Bayesian maximum entropy approach", *IEEE Trans. Signal Processing*, vol. 50, pp. 2333–2346, 2002.

[10] Y. V. Shkvarko and J. L. Leyva-Montiel, "Theoretical aspects of array radar imaging via fusing the experiment design and regularization techniques," in *Proc. SAM2002 Second IEEE Sensor Array Multichannel Signal Processing International Workshop,* (CD-ROM), 2002.

[11] F.G. Gallegos-Funes and V.I. Ponomaryov, "Real-time image filtering scheme based on robust estimators in presence of impulsive noise", *Real Time Imaging VII*, Elsevier Publ., pp. 69-80, 2004.

[12] I. Chudinovich, C. Constanda, and J. Colin Venegas, "Solvability of initial-boundary value problems for bending of thermoelastic plates with mixed boundary conditions," *Journal of Math. Anal. Appl.*, **311**, pp. 357-376, 2005.