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Intelligent Processing of Remote Sensing Imagery for Decision Support in Environmental Resource Management: A Neural Computing Paradigm

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***Abstract*–In this study, we propose a new neural network (NN) computational paradigm to resolve the resource management decision support (DS) oriented problems based on reconstructive remote sensing (RS) imaging with the use/fusion of multi-sensor systems as required for enhanced DS in environmental resource management and other related fields in DS technologies. The developed NN paradigm addresses a framework for resolving the computational problems related to the end-user DS in environmental monitoring based on the intelligent RS image reconstruction/enhancement.**

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

I. INTRODUCTION

Modern applied theory of reconstructive signal and image processing for environmental monitoring and resource management is now a mature and well developed research field, presented and detailed in many works, (see for example, [1] - [9] and the references therein). Although the existing theory offers a manifold of statistical and descriptive regularization techniques to tackle with the particular environmental resource management problems in many application areas there still remain some unresolved crucial theoretical and data processing problems related particularly to the decision support (DS) and end-user computing aspects of environmental resource management that incorporate the intelligent fusion of multi-sensor remote sensing (RS) imagery. In this study, we propose a new neural network (NN) computational paradigm to resolve the resource management DS-oriented problems based on reconstructive RS imaging with the use/fusion of multi-sensor systems as required for enhanced DS in environmental resource management and other related fields in DS technologies. The developed NN paradigm addresses a framework for resolving the computational problems related to the end-user DS in environmental monitoring based on the intelligent RS image reconstruction/enhancement. Particularly, two still unresolved general problems of a prime theoretical and computational importance for DS in environmental resource management based on intelligent computer-aided post-processing of the RS imagery are treated in details in this study, namely:

1) development of the theoretically-grounded DS-oriented randomized numerical model of a multi-sensor RS imaging experiment via combining the maximum entropy (ME) principle of information theory and regularization concept for alleviating the ill-poseness of the inverse problem of the high-resolution reconstruction of the RS scene images via digital (e.g. computer-aided) post processing of the initial rough RS images formed applying the conventional matched spatial filtering techniques [1];

2) design of a new numerical paradigm for *optimal* solving the DS-oriented inverse problem of the RS image reconstruction/enhancement with sensor fusion (*optimal* being considered in the fused maximum entropy (ME)-regularization setting) that incorporates the NN-based computing for the numerical implementation of the RS image enhancement techniques as required for the efficient DS in environmental resource management.

II. PHENOMENOLOGY

According to the mathematical statement [2], [4], [8], to perform the image enhancement via NN-based signal processing of the RS data employing the system/method fusion approach one have to solve the ME conditional optimization problem

$$\hat{\mathbf{v}} = \arg\min_{\mathbf{v}} E(\mathbf{v}\,|\,\boldsymbol{\lambda}) \tag{1}$$

of minimizing the cost (energy) function

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

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 [8] 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 [5]. 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) and $\mathbf{n}^{(m)}$ represents the noise in the actually acquired corresponding mth image, respectively.

In the 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 $\mathrm{E}(\mathbf{v}|\boldsymbol{\lambda})$ 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 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 result in the technically intractable fusion scheme if solve this problem employing the standard direct minimization techniques [3]. 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].

III. NN FOR INTELLIGENT IMAGE ENHANCEMENT WITH SENSOR FUSION

The dynamic NN, which we employ to solve the problem (1) is a modification of the maximum entropy NN (MENN), which was proposed in our previous studies [7], [8]. 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 proposed in [8].

Consider the multistate Hopfield-type (i.e. dynamic) NN [2], [4] with the K-D state vector $\mathbf{x}$ and K-D output vector $\mathbf{z}=\mathrm{sgn}(\mathbf{W}\mathbf{x} + \boldsymbol{\theta})$, 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]

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

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 IR systems to be fused:

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

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

for all $k, i = 1, \ldots, K$. To find a minimum of the energy function E, the states of the network should be updated $\mathbf{x}^{\prime\prime}=\mathbf{x}^{\prime}+\Delta\mathbf{x}$ using the update rule $\Re(\mathbf{z})$ developed in our previous study […] for computing a change $\Delta\mathbf{x}$ of the state vector $\mathbf{x}$, where the superscripts $'$ and $''$ correspond to the state values before and after network state updating (at each iteration), respectively.

While implementing the MENN algorithm developed in [8], the values of the regularization parameters may be chosen empirically as it was performed in [7] or controlled applying the aggregation schemes proposed in our previous studies [8], [9]. Hence, integrating the aggregation method [8] with the NN given by (4), (5), we derive the following scheme for adaptive (i.e. intelligent) adjustment of the weighting parameters in (4)

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

where $r_{\mathrm{m}} = \mathrm{trace}\{(\mathbf{F}^{(m)})^{-2}\}$ is the corresponding system's resolution factor, and $\hat{\omega}$ is to be found as a solution to the balance equation (equation (13) from [8]). Note that by integrating the presented above MENN algorithm with two optimization methods for optimal data aggregation developed in [8] other different modifications of the MENN-based system fusion algorithm developed here can also be proposed.

IV. COMPUTER SIMULATIONS

The simulation of the proposed method was 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 16 pixels width at half maximum, and PSF_2 of a squared "sinc" shape of 16 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 - 3. Also, we simulated the results of image enhancement without system fusion, which employed the inverse filtering techniques [1], [3] 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 dimension without optimal data aggregation were also reported in our previous works [7], [9].

Figure 1. Simulation results: degraded image formed by the 1st system.

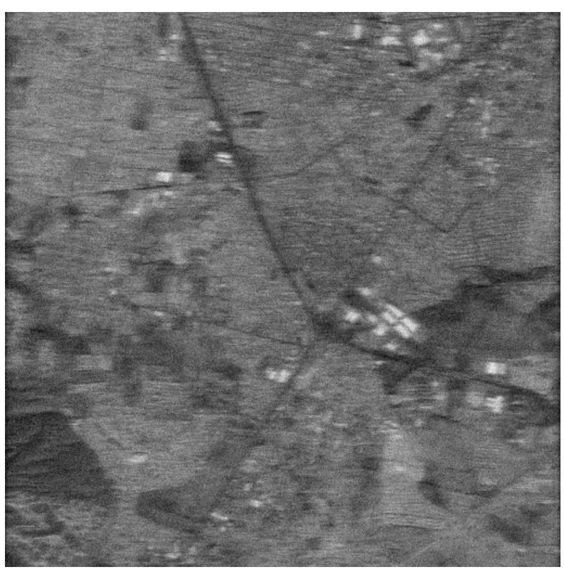

Figure 2. Simulation results: degraded image formed by the 2nd system.

Figure 3. Simulation results: reconstructed aggregated fused image.

V. CONCLUDING REMARKS

In this work, we addressed a novel look at the DS-oriented reconstructive signal and RS image processing as ill-conditioned inverse problems with model uncertainties. We extend the theory presented in [1] - [9] by developing the aggregated ME-NN-based regularization paradigm for reconstructive RS signal and image processing with system fusion subject to the regularization constraints imposed on the solution. The principal innovation that we address in the present study relates to further development of the new NN-computing-based paradigm (originally proposed in [7], [8]) and design of some new nonlinear numerical techniques for DS-oriented reconstructive data processing with particular application to DS in environmental resource management that employs the computer-aided post-processing of multi-sensor RS imagery. We include some simulation examples to illustrate the overall performances of the proposed approach. Our study is intended to establish the foundation to assist in understanding the basic theoretical aspects of the multi-level optimization (sensor fusion – regularized robust NN-based data post processing) for solving the reconstructive signal and image inverse problems as required for particular DS applications in environmental resource management, although, the results can be extended to other application areas.

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