



Memory-Augmented Model-Driven Network for Pan-sharpening

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Contributions

Our main contributions are summarized in the following three aspects:

- By extending the iterative algorithm into a multistage solution that combines the benefits of both model-based and data-driven deep learning techniques, we present a novel interpretable memory-augmented model-driven network (MMNet) for Pan-sharpening. The interpretation of the deep model is enhanced by such a design.

- To address the significant information loss problem in the signal flow, we suggest a new memory mechanism which is orthogonal to signal flow and develop a non-local cross-modality module. Such a design enhances the deep model's capacity for representation.

- Extensive experiments over three satellite datasets demonstrate that our proposed network outperforms other state-of-the-art algorithms both qualitatively and quantitatively.

Proposed approach

Model formulation:

The degradation process by using the maximum a posterior principle can be reformulated as:

$$\max_{\mathbf{H}} \frac{1}{2} \|\mathbf{L} - \mathbf{DKH}\|_2^2 + \eta \Omega_l(\mathbf{H}|\mathbf{P}) + \lambda \Omega_{NL}(\mathbf{H}|\mathbf{P})$$

We solve the optimization problem using half-quadratic splitting (HQS) algorithm:

$$\min_{\mathbf{H}, \mathbf{U}, \mathbf{V}} \frac{1}{2} \|\mathbf{L} - \mathbf{DKH}\|_2^2 + \frac{\eta_1}{2} \|\mathbf{U} - \mathbf{H}\|_2^2 + \eta_2 \Omega_l(\mathbf{U}|\mathbf{P}) + \frac{\lambda_1}{2} \|\mathbf{V} - \mathbf{H}\|_2^2 + \lambda \Omega_{NL}(\mathbf{V}|\mathbf{P})$$

Updating \mathbf{U} , \mathbf{V} , and \mathbf{H} alternately:

Updating \mathbf{U}

$$\mathbf{U}^{(k)} = \arg \min_{\mathbf{U}} \frac{\eta_1}{2} \|\mathbf{U} - \mathbf{H}^{(k)}\|_2^2 + \eta_2 \Omega_l(\mathbf{U}|\mathbf{P})$$

$$\mathbf{U}^{(k)} = \text{prox}_{\Omega_l(\cdot)} \left(\mathbf{U}^{(k-1)} - \delta_1 \nabla f_1(\mathbf{U}^{(k-1)}) \right)$$

$$\nabla f_1(\mathbf{U}^{(k-1)}) = \mathbf{U}^{(k-1)} - \mathbf{H}^{(k)}$$

Updating \mathbf{V}

$$\mathbf{V}^{(k)} = \arg \min_{\mathbf{V}} \frac{\lambda_1}{2} \|\mathbf{V} - \mathbf{H}^{(k)}\|_2^2 + \lambda \Omega_{NL}(\mathbf{V}|\mathbf{P})$$

$$\mathbf{V}^{(k)} = \text{prox}_{\Omega_{NL}(\cdot)} \left(\mathbf{V}^{(k-1)} - \delta_2 \nabla f_2(\mathbf{V}^{(k-1)}) \right)$$

$$\nabla f_2(\mathbf{V}^{(k-1)}) = \mathbf{V}^{(k-1)} - \mathbf{H}^{(k)}$$

Updating \mathbf{H}

$$\begin{aligned} \mathbf{H}^{(k+1)} = \arg \min_{\mathbf{H}} & \frac{1}{2} \|\mathbf{L} - \mathbf{DKH}\|_2^2 \\ & + \frac{\eta_1}{2} \|\mathbf{U}^{(k)} - \mathbf{H}\|_2^2 \\ & + \frac{\lambda_1}{2} \|\mathbf{V}^{(k)} - \mathbf{H}\|_2^2 \end{aligned}$$

$$\mathbf{H}^{(k+1)} = \mathbf{H}^{(k)} - \delta_3 \nabla f_3(\mathbf{H}^{(k)})$$

$$\begin{aligned} \nabla f_3(\mathbf{H}^{(k)}) = & (\mathbf{DK})^T (\mathbf{DKH}^{(k)} - \mathbf{L}) \\ & + \eta_1 (\mathbf{H}^{(k)} - \mathbf{U}^{(k)}) \\ & + \lambda_1 (\mathbf{H}^{(k)} - \mathbf{V}^{(k)}), \end{aligned}$$

