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END-TO-END SHALLOW NETWORK FOR VARIATIONAL PANSHARPENING

Marc Tomás-Cruz, Jamila Mifdal, Bartomeu Coll, Joan Duran[1]

[1]Universitat de les Illes Balears

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Abstract

Pansharpening aims to fuse the geometry of a high-resolution panchromatic image with the color information of a low-resolution multispectral image to generate a high-resolution multispectral image. Classical variational methods are more interpretable and flexible than pure deep learning approaches, but their performance is limited by the use of rigid priors. In this paper, we efficiently combine both techniques by introducing a shallow residual network to learn the regularization term of a variational pansharpening model. The proposed energy includes the classical observation model for the multispectral data and a constraint to preserve the geometry encoded in the panchromatic. The experiments demonstrate that our method achieves state-of-the-art results.

Variational Model

- We model the pansharpening problem as the minimization of the following energy function:

$$\min_{\mathbf{U}} \frac{\mu}{2}\|\mathbf{DBU}-\mathbf{M}\|_F^2 + \frac{\lambda}{2}\|\mathbf{U}\circ\tilde{\mathbf{P}} - \widetilde{\mathbf{U}}\circ\mathbf{P}\|_F^2 + R(\mathbf{U}) \tag{1}$$

- The second term is a constraint originally proposed in [2] that injects the geometry of the PAN data in the fused product.

$$\mathbf{U}-\widetilde{\mathbf{U}} = (\widetilde{\mathbf{U}}\oslash\tilde{\mathbf{P}})\circ(\mathbf{P}-\tilde{\mathbf{P}}), \tag{2}$$

- We rewrite the problem in a saddle-point formulation in order to find a global explicit solution using the first order Chambolle-Pock algorithm [1].

$$\begin{aligned}\min_{\mathbf{U}}\max_{\mathbf{V},\mathbf{W}} &\langle \mathbf{V},\mathbf{U}\rangle - R^*(\mathbf{V}) + \langle \mathbf{U}, \mathbf{B}^T\mathbf{D}^T\mathbf{W}\rangle \\ &- \langle \mathbf{M},\mathbf{W}\rangle - \frac{1}{2\mu}\|\mathbf{W}\|_2^2 + \frac{\lambda}{2}\|\mathbf{U}\circ\tilde{\mathbf{P}} - \widetilde{\mathbf{U}}\circ\mathbf{P}\|_F^2.\end{aligned} \tag{3}$$

- To approximate the proximity of the regularization function with a residual network, we apply Moreau's identity to $\text{prox}_{\gamma R^*}$ thus obtaining the following iterative scheme.

$$\begin{aligned}\mathbf{V}^{k+1} &= \mathbf{V}^k + \gamma\overline{\mathbf{U}}^k - \gamma\,\text{prox}_{\frac{1}{\gamma}R}\left(\tfrac{1}{\gamma}\mathbf{V}^k + \overline{\mathbf{U}}^k\right)\\ \mathbf{W}^{k+1} &= \frac{1}{1+\frac{\gamma}{\mu}}\left(\mathbf{W}^k + \gamma\left(\mathbf{DB}\overline{\mathbf{U}}^k - \mathbf{M}\right)\right)\\ \mathbf{U}^{k+1} &= \left(\mathbf{U}^k - \tau(\mathbf{V}^{k+1} + \mathbf{B}^T\mathbf{D}^T\mathbf{W}^{k+1} \right.\\ &\quad \left. - \lambda\tilde{\mathbf{P}}\circ\mathbf{P}\circ\widetilde{\mathbf{U}})\right)\oslash\left(1+\tau\lambda(\tilde{\mathbf{P}}\circ\tilde{\mathbf{P}})\right)\\ \overline{\mathbf{U}}^{k+1} &= \mathbf{U}^{k+1} + \theta\left(\mathbf{U}^{k+1}-\mathbf{U}^k\right),\end{aligned} \tag{4}$$

- Based in this iterative scheme, we can obtain a generalized model using a deep learning approach to compute the proximity of the regularizer function.

Model Architecture

Algorithm

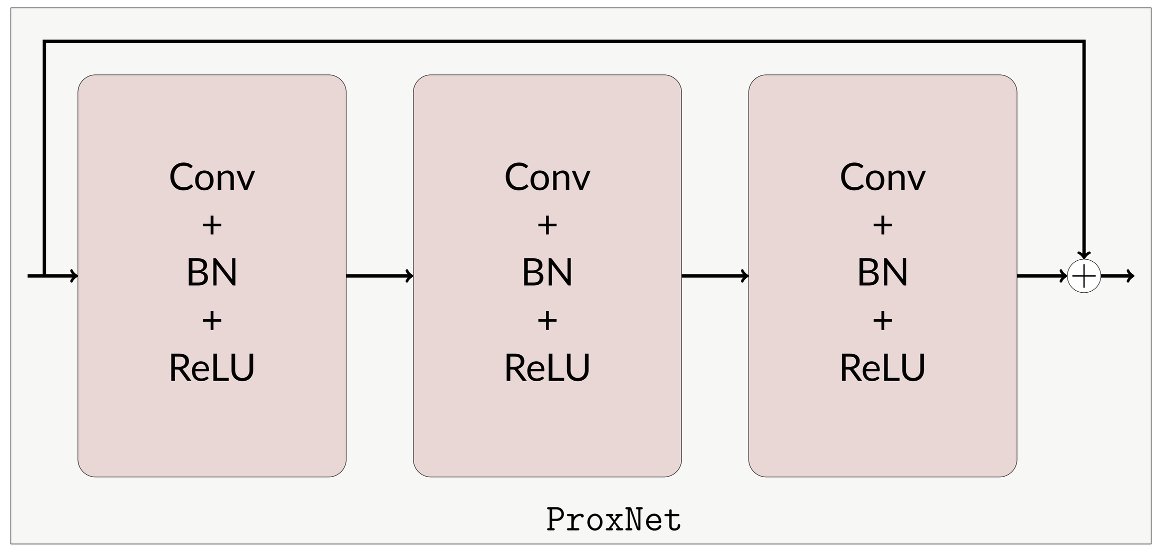
Input: Data: $\mathbf{M}$, $\mathbf{P}$, $\tilde{\mathbf{P}}$, $\widetilde{\mathbf{U}}$; Operators: $\mathbf{D}$, $\mathbf{B}$.

for *k* ← *0 to Niters* **do**

$$\begin{aligned}\mathbf{V}^{k+1} &= \mathbf{V}^k + \gamma\overline{\mathbf{U}}^k - \gamma\,\texttt{ProxNet}_\Theta\left(\tfrac{1}{\gamma}\mathbf{V}^k + \overline{\mathbf{U}}^k\right)\\ \mathbf{W}^{k+1} &= \frac{1}{1+\frac{\gamma}{\mu}}\left(\mathbf{W}^k + \gamma\left(\mathbf{DB}\overline{\mathbf{U}}^k - \mathbf{M}\right)\right)\\ \mathbf{U}^{k+1} &= \left(\mathbf{U}^k - \tau(\mathbf{V}^{k+1} + \mathbf{B}^T\mathbf{D}^T\mathbf{W}^{k+1} \right.\\ &\quad \left. -\lambda\tilde{\mathbf{P}}\circ\mathbf{P}\circ\widetilde{\mathbf{U}})\right)\oslash\left(1+\tau\lambda(\tilde{\mathbf{P}}\circ\tilde{\mathbf{P}})\right)\\ \overline{\mathbf{U}}^{k+1} &= \mathbf{U}^{k+1} + \theta\left(\mathbf{U}^{k+1}-\mathbf{U}^k\right)\end{aligned}$$

end

Output: $\mathbf{U}$



Quantitative Results

We compare our model with several state-of-the-art methods, distinguishing between classical and deep learning methods.

	#Params ($\cdot 10^4$)	PSNR ↑	SSIM ↑	SAM ↓
Bicubic	-	29.27	0.8505	0.0534
PCA	-	29.75	0.9246	0.2091
Brovey	-	35.23	0.9691	0.0561
GS	-	33.83	0.9511	0.0729
GSA	-	34.91	0.9549	0.0727
IHS	-	33.80	0.9504	0.0731
SFIM	-	32.09	0.9401	0.0551
DiCNN	4.22	37.81	0.9796	0.0275
MSDCNN	18.99	38.68	0.9826	**0.0243**
GPPNN	119.81	27.67	0.9466	0.0485
Ours	**1.15**	**40.81**	**0.9856**	0.0313

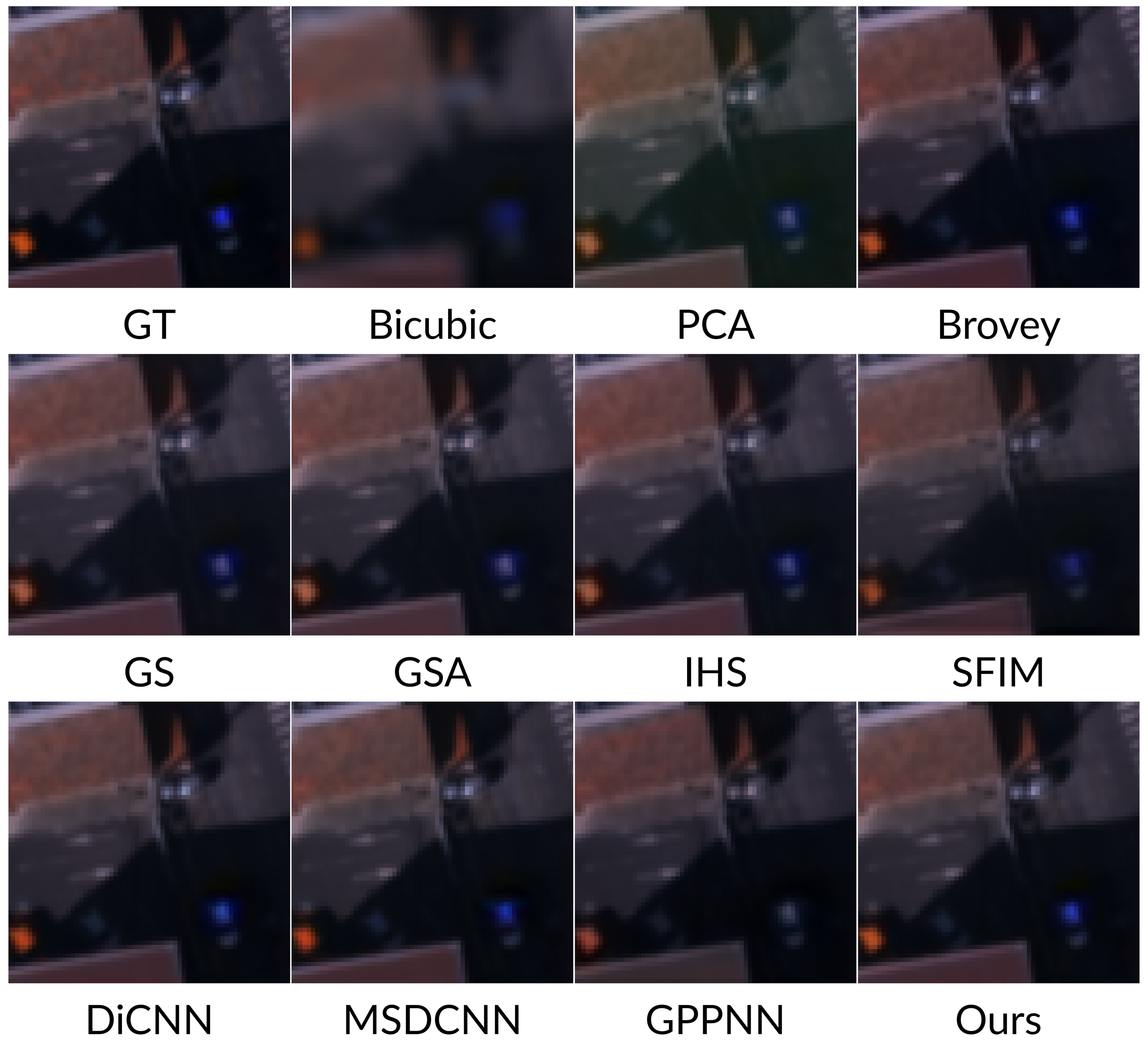
In addition, we test the robustness against noise of the different deep learning methods, using the bicubic interpolation as a reference of the results.

	PSNR ↑	SSIM ↑	SAM ↓
Bicubic	26.63	0.7250	0.1227
DiCNN	31.69	0.8708	0.1377
MSDCNN	31.46	0.8629	0.1298
GPPNN	26.31	0.9242	**0.0756**
Ours	**35.66**	**0.9384**	0.0867

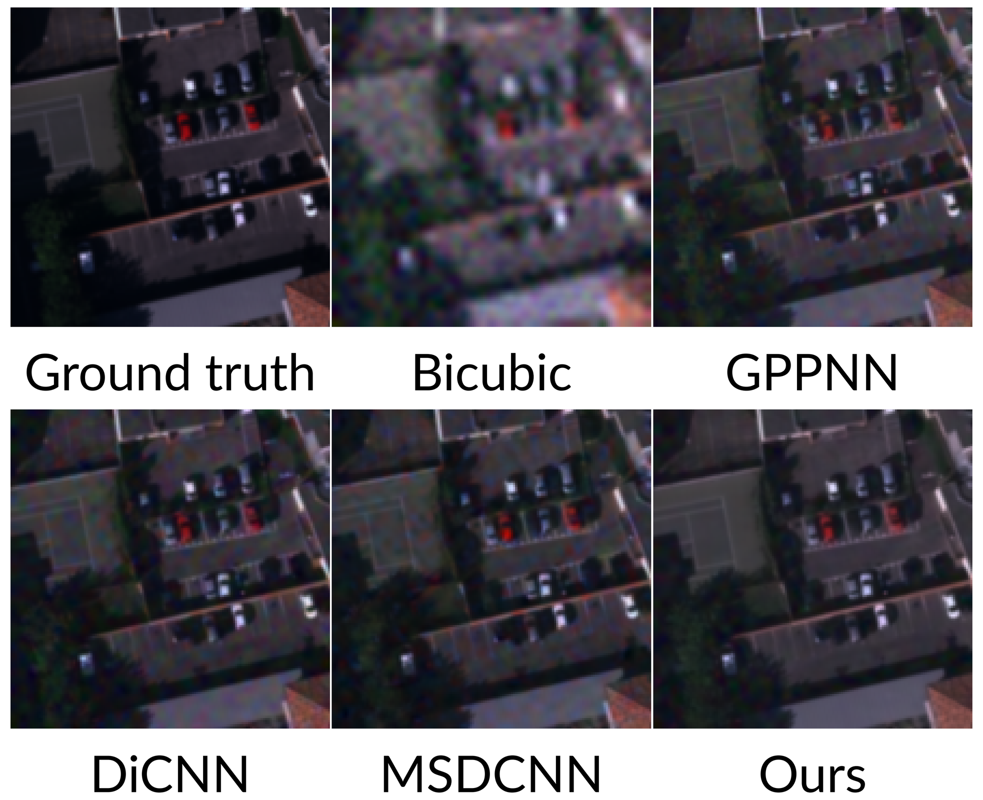
Our model achieves both state-of-the-art results and robustness against noise.

Qualitative Results

Different methods



Noise Robustness



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References

[1] A. Chambolle and T. Pock. A first-order primal-dual algorithm for convex problems with applications to imaging. *J. Math. Imaging Vis.*, 40(1):120–145, 2011.

[2] J. Duran, A. Buades, B. Coll, C. Sbert, and G. Blanchet. A survey of pansharpening methods with a new band-decoupled variational model. *ISPRS J. Photogramm. Remote Sens.*, 125:78–105, 2017.

marctomascruz@gmail.com