Superresolving Sentinel-2 Using Learned Multispectral Regularization

Sveinn Eirikur Armannsson, Magnus O. Ulfarsson, Johannes R. Sveinsson, Jakob Sigurdsson

Faculty of Electrical and Computer Engineering, University of Iceland

UNIVERSITY OF ICELAND

Introduction

Model based superresolution methods have proved useful for sharpening Sentinel-2 (S2) images to their maximum resolution. In this paper, an unrolled model based method to superresolve S2 images is proposed and unsupervised single image training is performed using reduced scale data. The method is evaluated using real and simulated data.

Method

Algorithm unrolling is a way of building efficient, interpretable neural networks by reimplementing traditional algorithms in a neural network context. Using an observational model we describe the acquisition of each S2 band as

$$\mathbf{y}_b = \mathbf{M}_b\mathbf{B}_b\mathbf{x}_b + \boldsymbol{\epsilon}, \quad (1)$$

where $\mathbf{y}_b$ is the vectorized captured image, $\mathbf{M}_b$ is a downsampling operator, $\mathbf{B}_b$ is a circulant blurring matrix, $\mathbf{x}_b$ is the vectorized n pixel target image and $\boldsymbol{\epsilon}$ is noise, each at band b.
Regularized sharpening is performed by minimizing the cost function

$$J(\mathbf{x}_b) = \frac{1}{2}\|\mathbf{M}_b\mathbf{B}_b\mathbf{x}_b - \mathbf{y}\|_2^2 + \frac{\lambda_b}{2}r(\mathbf{X}), \quad (2)$$

with respect to $\mathbf{x}$. Here r is a regularization function, λ_b is a tuning parameter, $\mathbf{X}$ is the target image across all bands, and L is the number of bands. An optimized solution for (2) is found using the method of steepest descent, where each step solves

$$\mathbf{x}_{i+1} = \mathbf{x}_i - \boldsymbol{\beta}\left[\mathbf{B}^\top\mathbf{M}^\top(\mathbf{M}\mathbf{B}\mathbf{x}_{i-1} - \mathbf{y}) + \boldsymbol{\Lambda}\mathbf{G}^\top\mathbf{G}\tilde{\mathbf{x}}\right], \quad (3)$$

where $\tilde{\mathbf{x}} = \left(\mathbf{1}_L^\top \otimes \mathbf{x}_i^\top\right)^\top$, $\mathbf{y} = \left(\left[\mathbf{y}_b^\top\right]_{b=1}^{L}\right)^\top$ and $\mathbf{M}$, $\mathbf{B}$, $\mathbf{G}$, and $\boldsymbol{\Lambda}$ are block diagonals and arrange downsampling operators, blur kernels, regularization filters, and tuning parameters, respectively, such that each $\mathbf{M}_b$, $\mathbf{B}_b$, $\mathbf{G}_b$, and λ_b line up with $\mathbf{x}_b$. The diagonal parameter matrix $\boldsymbol{\beta}$ controls the step size for each band independently. This iterative algorithm is unrolled into a layered network representation that consists of a finite number of stacked layers that each solve (3) as seen in Figure 1.

Architecture

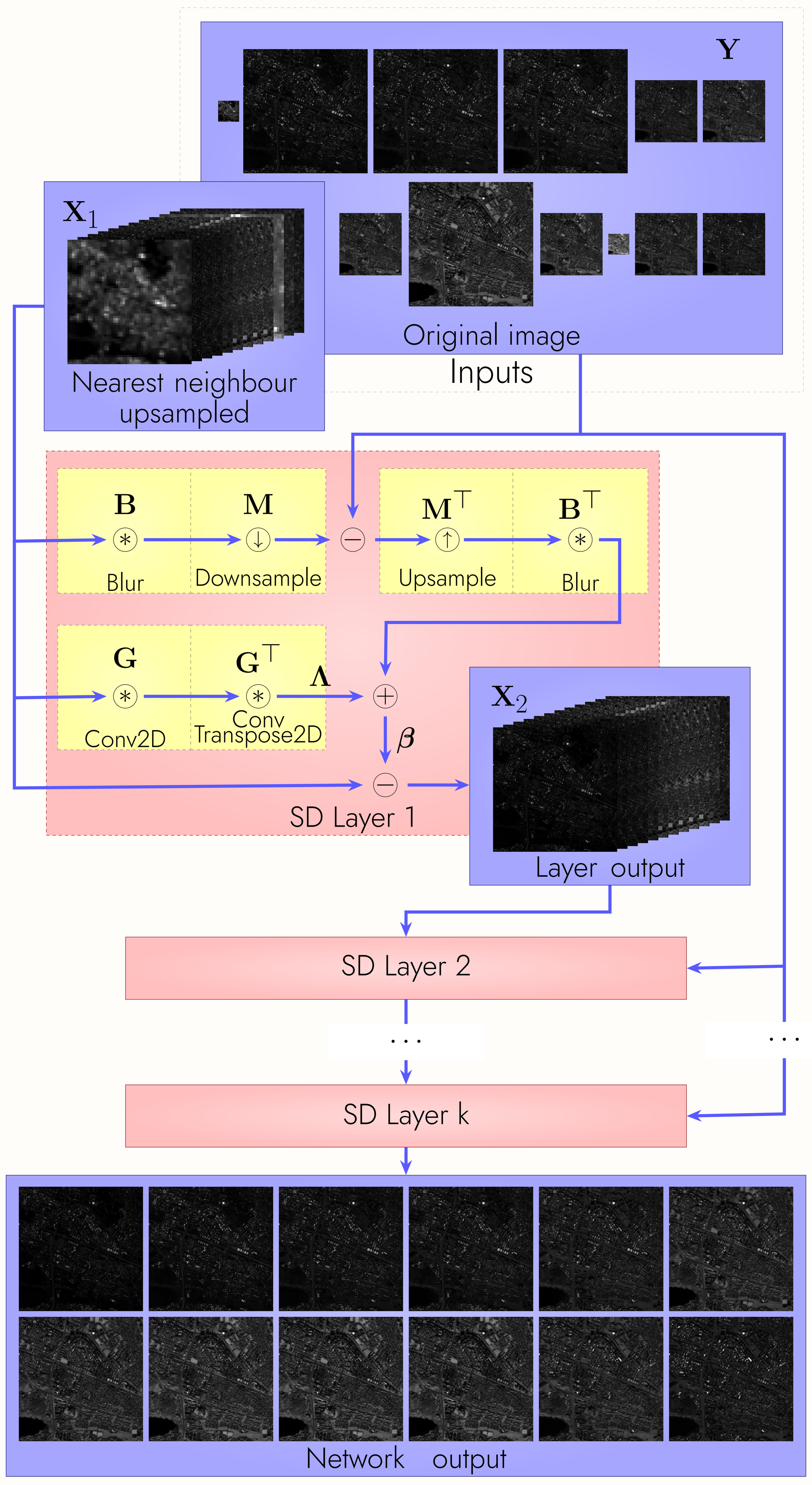

Figure 1: The network architecture.

Each layer learns its own filters, $\mathbf{G}$, and tuning parameters, $\boldsymbol{\Lambda}$ and $\boldsymbol{\beta}$. Suitable regularization filters and parameters are found using gradient descent and a stochastic optimization scheme.

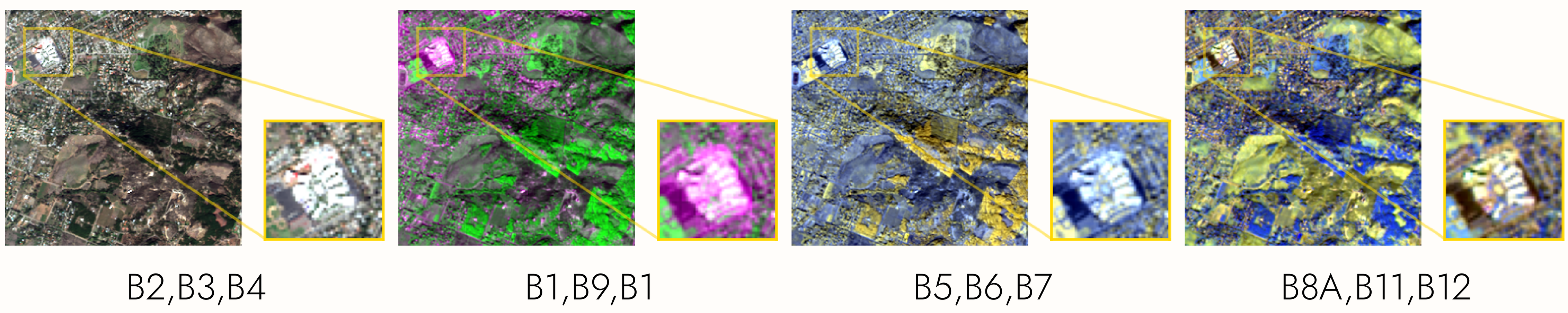

Figure 2: False color composites from a super resolved synthetic S2 image taken over Escondido, California.

Results

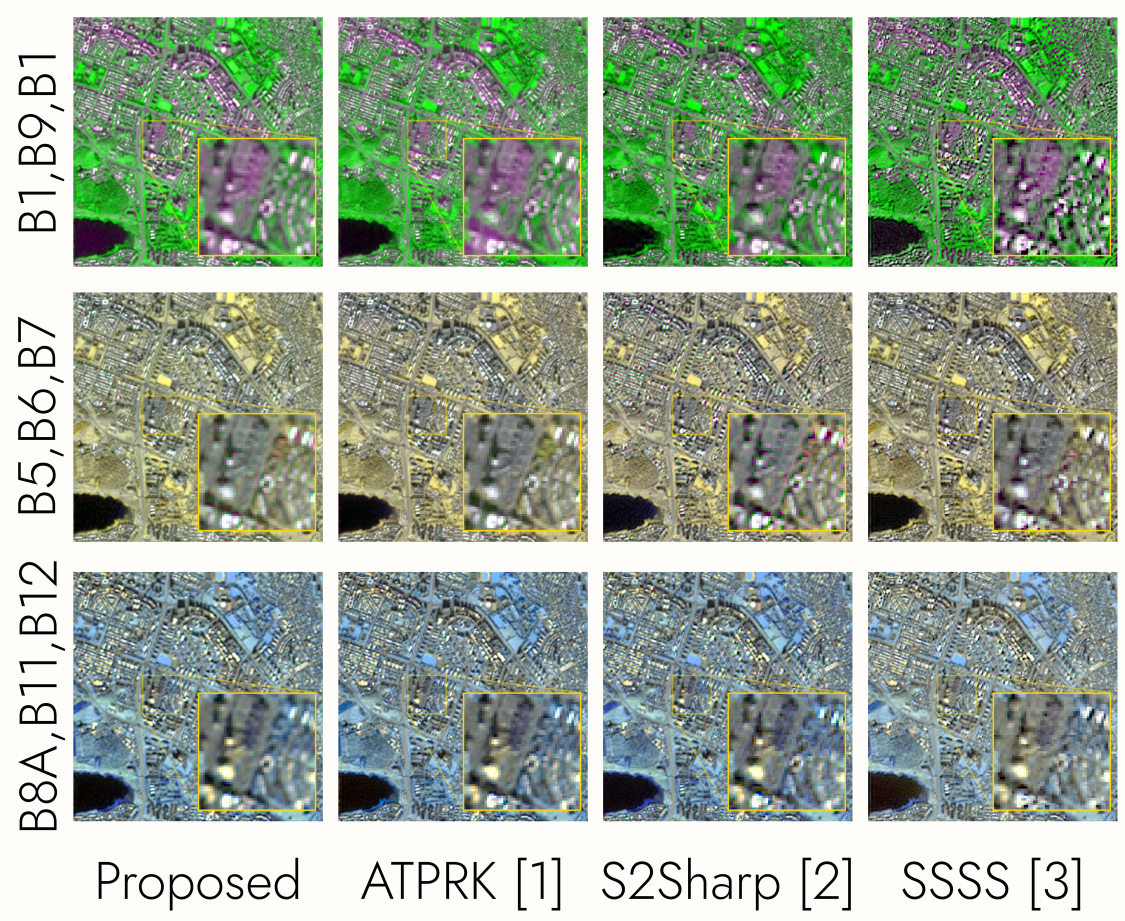

Figure 3: False color composites from a super resolved S2 image taken over Reykjavik, Iceland.

Four synthetic S2 images from [3] were processed and evaluated against ground truth. Table 1 shows a comparison of six different quantitative image quality metrics.

Conclusions

An unrolled superresolution method for Sentinel-2 is proposed and shown to give comparable results to traditional model based methods. The ability to easily change the loss functions and training methods offers many possibilities for further improvements.

References

[1] Q. Wang et al., "Area-to-point regression kriging for pan-sharpening," *ISPRS Journal of Photogrammetry and Remote Sensing*, 2016.

[2] M. O. Ulfarsson et al., "Sentinel-2 Sharpening Using a Reduced-Rank Method," *IEEE Transactions on Geoscience and Remote Sensing*, 2019.

[3] C.-H. Lin and J. M. Bioucas-Dias, "An Explicit and Scene-Adapted Definition of Convex Self-Similarity Prior With Application to Unsupervised Sentinel-2 Super-Resolution," *IEEE Transactions on Geoscience and Remote Sensing*, 2020.

Table 1: SRE, RMSE, SAM, SSIM, UIQI and ERGAS, arrows indicate whether higher or lower values are better, **best** results in bold, *second best* italicised.

	SRE ↑			RMSE ↓			SAM ↓		SSIM ↑			UIQI ↑			ERGAS ↓	
Method	All	20 m	60 m	All	20 m	60 m	20 m	All	All	20 m	60 m	All	20 m	60 m	20 m	60 m
ATPRK	**30.36**	**33.24**	21.71	52.90	**28.10**	93.25	**1.19**	1.75	**0.99**	**0.99**	*0.97*	0.81	**0.86**	0.67	**1.80**	1.96
S2Sharp	*29.55*	*29.49*	**29.73**	**41.17**	*41.57*	**39.77**	2.26	*1.61*	**0.99**	**0.99**	**0.99**	*0.82*	*0.82*	*0.82*	*2.24*	**0.63**
SSSS	21.82	23.34	17.28	109.43	80.43	167.81	1.85	2.59	*0.97*	*0.97*	0.91	0.72	0.78	0.53	4.57	2.89
Proposed	*29.60*	*30.34*	*27.36*	*43.19*	*39.01*	*51.44*	*1.47*	**1.29**	**0.99**	**0.99**	**0.99**	**0.86**	**0.86**	**0.88**	*2.11*	*0.85*