On Spatial Priors for Satellite Image Fusion

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***Abstract*—Different spatial priors for satellite image fusion are evaluated through experiments on three different data sets. The results are judged visually as well as quantified via different image quality metrics on a down-sampled data-set. It is done within our previously proposed spectrally consistent pansharpening framework (SCP). This is a per pixel based fusion framework constructed by considering the imaging physics.**

I. Introduction

Several widely used methods have been proposed for fusing high resolution panchromatic data and lower resolution multichannel data. However, many of these methods fail to maintain spectral consistency of the fused high resolution image, which is of high importance to many of the applications based on satellite data. Additionally, most of the methods we are acquainted with are loosely connected to the image forming physics of the satellite images, giving these methods an ad hoc feel. In [8] Vesteinsson et al. we proposed a method for fusion of satellite images that is based on the properties of imaging physics in a statistically meaningful way. The fusion method is called spectral consistent pansharpening (SCP) and it was shown that spectral consistency was a direct consequence of imaging physics and hence guaranteed by the SCP. The spectral consistency was achieved while exploiting the high resolution single-channel data in what can be seen as a statistical optimal way. Specifically, the SPC is based on the observation, that any given channel of the satellites's imaging device can be seen as an inner-product between the radiated light arriving at the sensor and the spectral response function of that channel. This gives a simple inner product space encompassing the relationship between the different channels as well as imposing spectral consistency. Normal distributed statistics - inducing the same norm as the above mentioned inner product - is used for regularization. This yield´s a framework to which additional constraints are added in a straight forward manner. A highly useful category of such constraints are spatial, where a given pixel is related to its neighbours. In [1] Aanæs et al. we showed how such constraints could be added to the SCP framework while maintaining spectral consistency. This was done by constraining the resulting pixel values to a hyper plane dictated by the imaging physics.

A reason that such spatial constraints are useful is that satellite image fusion is inherently an ill-posed inverse problem, thus requiring additional constraints – implicitly or explicitly – to be solved. A good strategy for constructing such constraints is the use of ones prior assumptions or knowledge about the solution, e.g. that a cityscape tends to be piecewise smooth, and many of our priors about satellite images are spatial. In this work we investigate the use of spatial smoothing priors, where the degree of smoothing locally is based on the corresponding 'edges' in the high resolution single-channel. These spatial priors thus, in a sense, incorporates the notion of line process in the SCP framework, c.f. [3] Black and Rangarajan. The question, however, is how the relation between the degree of smoothing and the high resolution single-channel should be formulated. We, hence, specifically investigate different strategies for how the high resolution singlechannel image should control the local smoothing of the fused result, thus in essence trying to determine how to transferee edges between the images.

Table I
Various metrics comparing the original low resolution RGB image with a fused 'approximation' hereof based on down-sampled input data, i.e. pan-chromatic and low resolution RGB-image. The experiment is run on all three data sets with all the mentioned fusion strategies. The metrics are as follows **MSE** mean squared error on all bands **CC** mean cross-correlation between bands **WB** Mean Wang Bovith measure between bands [10] **SSIM** The mean of [9] on each band **Q4** An extension of Wang and Bovik to multiple dimensions giving a combined metric, by Alparone et al. [2].

	MSE	CC	WB	SSIM	Q4
IKONOS:					
No Weight	0.0024	0.9120	0.6437	1.0000	0.6513
Uniform Weight	0.0029	0.8946	0.6133	1.0000	0.6171
Line Induced	0.0025	0.9094	0.6388	1.0000	0.6425
Gradient Induced	**0.0021**	**0.9244**	**0.6874**	1.0000	**0.6957**
IHS Method	0.0026	0.8971	0.5523	*0.9999*	0.6386
QuickBird:					
No Weight	0.0008	0.9132	0.7087	1.0000	0.7086
Uniform Weight	0.0008	0.9145	0.6844	1.0000	0.6809
Line Induced	0.0008	0.9195	0.7147	1.0000	0.7137
Gradient Induced	**0.0007**	**0.9213**	**0.7227**	1.0000	**0.7287**
IHS Method	0.0132	0.6836	0.4470	*0.9990*	0.5217
Metrosat:					
No Weight	0.0037	0.9491	0.7144	1.0000	0.6915
Uniform Weight	0.0033	0.9458	0.6851	1.0000	0.6836
Line Induced	0.0033	0.9474	0.6993	1.0000	0.6927
Gradient Induced	**0.0030**	**0.9545**	**0.7366**	1.0000	**0.7334**
IHS Method	0.0114	0.9272	0.6277	*0.9992*	0.7293

II. Setting or Framework

The setting of our algorithm, as presented in [1], is that there is a per pixel term $\mathcal{D}_{ij}$, and a spatial smoothing term

Table II
SPECTRAL CONSISTENCY OF THE IHS METHOD, MEASURED AS THE CROSS CORRELATION BETWEEN THE LOW RESOLUTION RGB IMAGE AND THE APPROPRIATELY DOWN-SAMPLED FUSED IMAGE. FOR THE REST OF THE INVESTIGATED STRATEGIES THE WAS A PERFECT CORRELATION OF 1, AS WOULD BE EXPECTED SINCE THE METHODS ARE SPECTRALLY CONSISTENT BY DESIGN.

Data set	Spectral Consistency
IKONOS	0.9106
QuickBird	0.9414
Metrosat	0.9414

which are combined for each pixel i, j

$$\min \sum_{ij} \left(\mathcal{D}_{ij} + \gamma \sum_{k \in \mathcal{N}_{ij}} \rho(\epsilon_{ijk}) w_{ikj} \right) \quad , \qquad (1)$$

where k runs over the 4-neighbors of pixel i, j and$\rho(\epsilon_{ijk})$ is a scalar enumerating the difference between a pixel and its neighbor. What needs to be determined — and is the subject of this paper — is the associated weights w_{ijk}, which are set by processing the given pan-chromatic image and determines to what extent there should be an edge at pixel i, j. Lastly there is a weighting constant γ. The combined solution for the whole fused image is given by a large least squares system, where spectral consistency is ensured via the parametrization.

We investigate four different strategies for setting the weights, w_{ijk}, where the two first are mostly included for comparison purposes:

1) **No smoothing** i.e. all the weights are set to zero. This is included for comparison purposes.
2) **Uniform Weighting** i.e. all the w_{ijk} are equal.
3) **Line Induced Weighting** edges are extracted from the pan-chromatic image, here via the Canny Edge detector [4]. The weights are then set to 0 where there is an edge and 1 otherwise.
4) **Gradient Induced Weighting** Here we go the step further, and produce weights in the range from 0 to 1, depending on the gradient magnitude of the pan-chromatic image. Our investigation showed that a linear relationship between the weights and the gradient magnitude produced poor results. We thus applied a non-linear function, which has proven successful in line extraction in the non-linear diffusion framework, c.f. e.g. [11], namely the function proposed by Perona and Malik in [7].

These are compared to the IHS based image fusion method, c.f. e.g. [5], which is perhaps the most popular approach to the image fusion problem. Many more strategies could be envisioned, particularly combinations and variations of the above methods. We have however chosen these because they span the possible strategies well and the line and gradient induced weights give good results.

III. EXPERIMENTS

The contribution of this paper is an evaluation of the above mentioned strategies. We have done this by applying the these strategies to three different data-sets from three different satellite types depicting different types of landscape. Thus spanning the different types of data, satellite image fusion is used for, decently. The three data sets are:

1) **IKONOS** is an image of a cityscape taken by the IKONOS earth imaging satellite.
2) **QuickBird** is an image of a forest landscape bisected by roads and containing a few large buildings. This image is taken by the QuickBird satellite.
3) **Metrosat** Is a weather satellite depicting Europe from the Metrosat satellite [6].

There is to our knowledge, however, not a single good canonical metric for evaluating image fusion algorithms. Hence we have partly relied on a visual inspection of the fused results as seen in Figures 1, 2, 3 and 4. The lack of canonical image metrics does not mean that metrics do not exist, we have thus applied some of the more popular to a comparison between the original low sampled color image and a fused image based on an appropriately down sampled data set — thus in a sense giving us the ground truth, albeit on a different scale — for the result hereof c.f. Table I. Lastly, the methods based on our method are spectrally consistent, which does not hold for the IHS method. Thus the degree of spectral consistency for the IHS method is investigated c.f. Table II.

Judging by the image quality metrics, Table I, it is seen that the gradient induced weighting scheme produces the best results. This also corresponds well with our visual inspection of the different weighting schemes (i.e. not the IHS method). Here it is seen that the gradient and line induced schemes produce good results, although the line induced scheme gives a too segmented image. So the gradient induced scheme visually gives the best results, although it a bit blurry. So perhaps a mix between the line induced and the gradient induced scheme would give even better results.

Comparing with the IHS method it is visually seen that more high frequency detail is present in the image giving a 'sharper' result. The IHS method is however not spectrally consistent as seen in Table II. This lack of color consistency is also noted visually, in that the trees and grass become grayish in stead of green. Much of this high frequency information is also present with the no smoothing scheme, albeit at the cost of a significant blocking effect originating from the low resolution blocks. This is well in line with our current experience that suggests that *if* you want spectral consistency you *either* need a slightly blurred image (w.r.t. the pan-chromatic image) *or* endure a blocking effect.

IV. DISCUSSION AND CONCLUSION

Here different several spatial image prior strategies for satellite image fusion has been presented and compared to each other and the IHS method. It is shown that they yield good and spectral consistent results, albeit with the loss of some of the high frequency information in the panchromatic image. A prior based on inhomogeneous smoothing, inspired by the non-linear diffusion techniques c.f. e.g. [11], is the best choice for prior.

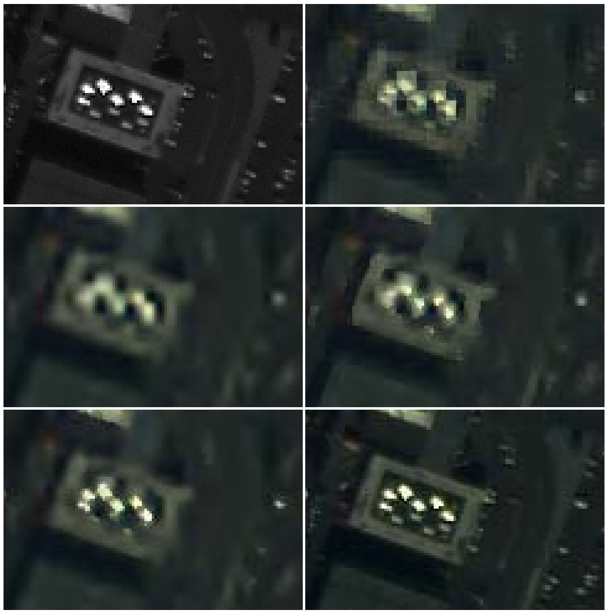

Figure 1. Results of the image fusion strategies. A sample of the resulting images on the IKONOS data set **top left:** Input Pan-chromatic image **top right:** No smoothing. **middle left:** Uniform Weights. **bottom left:** Line Induced Weighting **bottom right:** Gradient Induced Weighting.

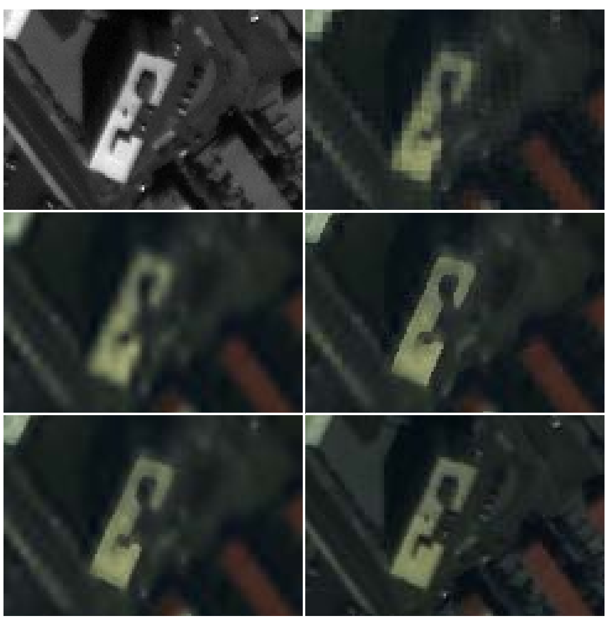

Figure 2. Results of the image fusion strategies. Another sample of the resulting images on the IKONOS data set **top left:** Input Pan-chromatic image **top right:** No smoothing. **middle left:** Uniform Weights. **bottom left:** Line Induced Weighting **bottom right:** Gradient Induced Weighting.

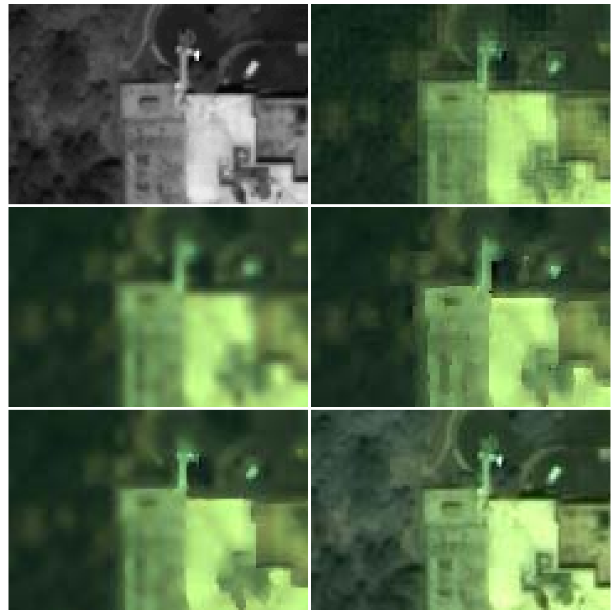

Figure 3. Results of the image fusion strategies. A sample of the resulting images on the QuickBird data set **top left:** Input Pan-chromatic image **top right:** No smoothing. **middle left:** Uniform Weights. **bottom left:** Line Induced Weighting **bottom right:** Gradient Induced Weighting.

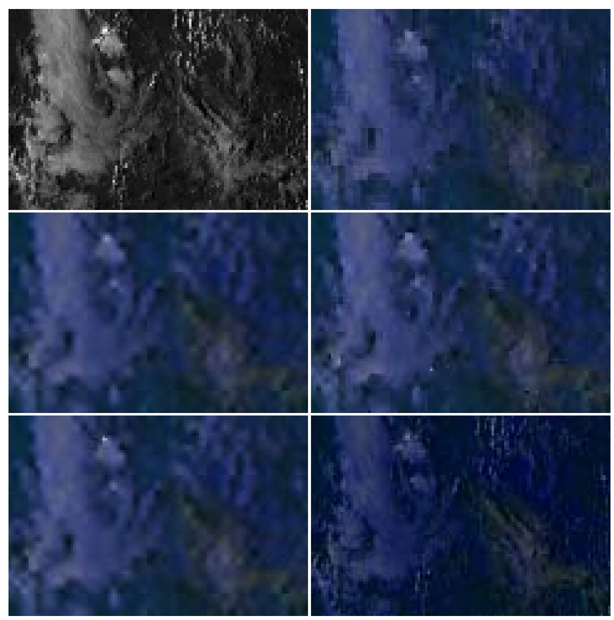

Figure 4. Results of the image fusion strategies. A sample of the resulting images on the Metrosat data set **top left:** Input Pan-chromatic image **top right:** No smoothing. **middle left:** Uniform Weights. **bottom left:** Line Induced Weighting **bottom right:** Gradient Induced Weighting.

REFERENCES

[1] H. Aanæs, J.R. Sveinsson, J.A. Nielsen, A.A.and Benediktsson, and T. Bøvith. Spectrally consistent satellite image fusion with improved image priors. *Submitted to: Proceedings of the 7th Nordic Signal Processing Symposium, NORSIG 2006*, 2006.

[2] L. Alparone, S. Baronti, A. Garzelli, and F. Nencini. A global quality measurement of pan-sharpened multispectral imagery. *IEEE Transactions on Geoscience and Remote Sensing Letters*, 4(1):313–317, 2004.

[3] M.J. Black and A. Rangarajan. On the unification of line processes, outlier rejection, and robust statistics with applications in early vision. *International Journal of Computer Vision*, 19(1):57–91, 1996.

[4] J. Canny. A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-8(6):679–698, 1986.

[5] T.W. Carper, T.M. Lillesand, and R.W. Kiefer. The use of intensity-

hue-saturation transformations for merging spot panchromatic and multi-spectral image data. *Photogrammetric Engineering and Remote Sensing*, 56(4):459–467, 1990.

[6] Schmetz J., Pili P., Tjemkes S., Just D., Kerkmann J., Rota S., and Ratier A. An introduction to Meteosat second generation (MSG). *Bulletin of the American Meteorological Society*, 83(7):977–992, 2002.

[7] P. Perona and J. Malik. Scale-space and edge detection using anisotropic diffusion. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(7):629–639, 1990.

[8] A. Vesteinsson, H. Aanæs, J.R. Sveinsson, and J.A. Benediktsson. Spectral consistent satellite image fusion: using a high resolution panchromatic and low resolution multi-spectral images. *Geoscience and Remote Sensing Symposium, 2005. IGARSS '05. Proceedings. 2005 IEEE International*, 4:2834–2837, 2005.

[9] Zhou Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. Image quality assessment: from error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612, 2004.

[10] Zhou Wang and Alan C. Bovik. A universal image quality index. *IEEE Signal Processing Letters*, 9(3):81–84, 2002.

[11] J. Weickert. *Anisotropic Diffusion in Image Processing*. ECMI Series. Teubner-Verlag, Stuttgart, Germany, 1998.