COMPRESSIVE SENSING FOR PAN-SHARPENING

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ABSTRACT

Based on compressive sensing framework and sparse reconstruction technology, a new pan-sharpening method, named *Sparse Fusion of Images* (SparseFI, pronounced as sparsify), is proposed in [1]. In this paper, the proposed SparseFI algorithm is validated using UltraCam and WorldView-2 data. Visual and statistic analysis show superior performance of SparseFI compared to the existing conventional pan-sharpening methods in general, i.e. rich in spatial information and less spectral distortion. Moreover, popular quality assessment metrics are employed to explore the dependency on regularization parameters and evaluate the efficiency of various sparse reconstruction toolboxes.

Index Terms — compressive sensing, pan-sharpening, dictionary training, sparse coefficients estimation

1. INTRODUCTION

The optical images acquired by most topographic earth observation satellites such as IKONOS, Quick Bird and GeoEye are composed of a panchromatic channel of high spatial resolution (e.g. 0.5 – 1m) and several (typically 3 - 8) multispectral channels at a lower spatial resolution (e.g. 2 – 4m). While the panchromatic image allows for accurate geometric analysis, the spectral channels provide the spectral information, necessary for thematic interpretation.

In order to fulfill application requirements, intensive research has been carried out to develop efficient pan-sharpening methods for generating multi-spectral images with spatial resolution of each channel as high as the panchromatic channel. Among a wide choice of pan-sharpening methods, the most popular ones are Intensity-Hue-Saturation technique (IHS) [2], Principal Components Analysis (PCA) [3], Brovey transform [4] and wavelet based fusion [5]. However, due to significantly different gray value between the panchromatic and the multispectral images caused by different observation wavelength ranges, these conventional methods may suffer from spectral distortion. Hence it calls for new sophisticated pan-sharpening methods which can produce high resolution multispectral images which are rich in spatial information and suffer less from spectral distortion.

Compressive sensing is a state-of-the-art signal processing technique. Its super-resolution capability and robustness have been demonstrated in different areas of signal and image processing [6][7]. This fact as well as the natural property of compressibility of remote sensing imagery inspired us to explore the potential of compressive sensing for pan-sharpening. Based on compressive sensing framework and sparse reconstruction technology, a new pan-sharpening method, named *Sparse Fusion of Images* (SparseFI, pronounced as sparsify), is proposed in [1]. With a given high-resolution (HR) panchromatic image and a corresponding low-resolution (LR) multispectral image as inputs, SparseFI works in three steps: a) dictionary learning; b) sparse coefficients estimation; c) HR multispectral image reconstruction to generate the desired HR multispectral image.

In this paper, the SparseFI algorithm is validated using UltraCam and WorldView-2 data. Visual and statistic analysis show superior performance of our method compared to the existing conventional pan-sharpening methods in general. Moreover, popular quality assessment metrics are employed to explore the dependency on regularization parameters and evaluate the efficiency of various sparse reconstruction toolboxes

2. THE SPARSEFI ALGORITHM FOR PAN-SHARPENING

Pan-sharpening requires a LR multispectral image $\mathbf{Y}$ and a HR panchromatic image $\mathbf{X}_0$, and aims at keeping the spectral information of $\mathbf{Y}$ and raising its spatial resolution, i.e. generating a HR multispectral image. SparseFI utilizes the HR spatial information of the pan image by generating a low resolution dictionary $\mathbf{D}_l$ and a HR dictionary $\mathbf{D}_h$ from small patches of the HR pan image and its appropriately down-sampled version. This strategy ensures $\mathbf{D}_l$ and $\mathbf{D}_h$ have the same coefficients while representing the identical HR and LR multispectral image patch, respectively. In addition, due to the fact that the dictionaries are built up from the pan image observing the same area, the multispectral image patches always can be described by a few non-zero or significant coefficients (i.e. a sparse representation) in these dictionary pair. Hence by means of an L_1-L_2 norm minimization, the sparse coefficients representing the LR multispectral image patches in the $\mathbf{D}_l$ can be accurately reconstructed. Since the coupled dictionaries share the same sparse coefficients while representing the corresponding image patch pairs, the HR multispectral image patches can be recovered in $\mathbf{D}_h$ with these coefficients. Finally, overlap region processing adjust the adjacent area and produce a seamless high resolution multispectral image. The detailed steps of SparseFI algorithm are explained as below:

a) Dictionary learning

The coupled high-resolution dictionary $\mathbf{D}_h$ and low-resolution dictionary $\mathbf{D}_l$ for reconstruction are produced by sampling the image patch pairs directly and simultaneously from the HR image $\mathbf{X}_0$ and its LR version $\mathbf{Y}_0$. LR image $\mathbf{Y}_0$ is generated by employing a low-pass filter to down-sample $\mathbf{X}_0$ to the size of $\mathbf{Y}$ with defined down-sampling factor F_{DS} (typically 4-10). Then the corresponding image $\mathbf{X}_0$ and $\mathbf{Y}_0$ are partitioned into coupled image patch pairs $\mathbf{x}_0$ and $\mathbf{y}_0$ with defined overlapping rate and sampling window size. For $\mathbf{Y}_0$, the window size is typically 3×3 to 9×9, depending on the image size and operational requirements; and for $\mathbf{X}_0$ is F_{DS} times less so that each HR patch corresponds to a LR patch. Then the dictionaries $\mathbf{D}_l$ and $\mathbf{D}_h$ are formed by normalizing the pixel values of $\mathbf{x}_0$ and $\mathbf{y}_0$ and arranging them into matrix columns, respectively.

b) Sparse Coefficients Estimation

The patches of the LR multispectral image Y are processed in raster-scan order. For each LR multispectral patch $\mathbf{y}$, a sparse coefficient vector $\hat{\boldsymbol{\alpha}}$ can be estimated by an L_1-L_2 minimization [8]

$$\hat{\boldsymbol{\alpha}} = \arg\min_{\alpha} \left\{ \lambda \|\boldsymbol{\alpha}\|_1 + \frac{1}{2}\left\|\tilde{\mathbf{D}}\boldsymbol{\alpha} - \tilde{\mathbf{y}}\right\|_2^2 \right\} \qquad (1)$$

where

$$\tilde{\mathbf{D}} = \begin{bmatrix} \mathbf{D}_l \\ \beta \mathbf{P}\mathbf{D}_h \end{bmatrix}, \ \tilde{\mathbf{y}} = \begin{bmatrix} \mathbf{y} \\ \beta \mathbf{w} \end{bmatrix} \qquad (2)$$

The parameter β is a weighting factor that gives a trade-off between goodness of fit of the LR input and the consistency of reconstructed adjacent HR patches in overlapping area. In our experiment β is chosen to be $1/F_{DS}^2$. The matrix $\mathbf{P}$ is a diagonal matrix that extracts the region of overlap between current target patch and previously reconstructed HR multispectral image. $\mathbf{w}$ contains the pixel values of the previously reconstructed HR multispectral image on the overlap region. λ is the standard Lagrangian multiplier, balancing the sparsity of the solution and the fidelity of approximation to $\mathbf{y}$.

c) HR multispectral image reconstruction

The desired sharpened HR image can finally be generated by tiling all HR multispectral patches $\boldsymbol{x}$ which are recovered by:

$$\hat{\mathbf{x}} = \mathbf{D}_h \hat{\boldsymbol{\alpha}} \qquad (3)$$

3. PERFORMANCE ASSESSMENT WITH REAL DATA

The proposed SparseFI algorithm is validated using two data sets provided by UltraCam and WorldView-2 both at the city of Roma. The results are compared to four conventional methods: the original IHS, adaptive IHS, PCA and Brovey transform. For quantitative comparison, several evaluation tests are carried out.

a) Validation of SpaseFI Algorithm

The data acquired by UltraCam is a multispectral image containing four channels (i.e. red, green, blue and near infrared) with a spatial resolution of 10 cm. In our experiment, the LR multispectral image $\mathbf{Y}$ is simulated by down-sampling the four channels, and the HR pan image $\mathbf{X}_0$ is simulated by adding some model error (e.g. set to be 2.7% in figure 1) to a linear combination of the four bands. In figure 1, the image (a) is the LR multispectral image down-sampled by a factor of 10 to a spatial resolution of 1m. Image (b) shows the reconstructed result of the proposed SparseFI algorithm. Compared to the results produced by conventional pan-sharpening methods, original IHS, adaptive IHS, PCA, and Brovey transform, it verifies the robustness of the compressive sensing based pan-sharpening method even under the situation of the large down-sampling factor of 10. However, in order to have an objective evaluation of overall image quality, quantitative assessment metrics are introduced for comparison (see Table 1).

The utilized assessment metrics include: root mean square error (RMSE) calculates the changes in pixel values to compare the difference between original image and pan-sharpened image; correlation coefficient (ρ) measures the similarity of spectral feature; degree of distortion (D) reflects the distortion level of pan-sharpened image; universal image quality index (UIQI), a widely used image sharpening quality assessment indicator recently; average gradient reflects the contrasts of details contained in the image as well as the image intelligibility; erreur relative dimensionless global error in synthesis (ERGAS) reflects the overall quality of pan-sharpened image.

The data acquired by WorldView-2 is a panchromatic image with a spatial resolution of 0.5m and a multispectral image with a spatial resolution of 2m at the same scene. It is down-sampled to a panchromatic image 2m and a multispectral image 8m to reconstruct a multispectral image with a spatial resolution of 2m, compared to the original multispectral image. Evaluation values are exhibited in Table 2.

The second rows of Table 1 and Table 2 list the optimal values of evaluation criteria. The best value is highlighted for each test. Our SparseFI scores the best among all pan-sharpening methods, especially with smaller ERGAS value indicates less spectral distortion.

b) Dependency on Regularization Parameter λ

λ is the well-known Lagrangian multiplier. It balances the sparsity of the solution and the fidelity of the approximation to **y**, and guarantees the robust image reconstruction from noisy data. Due to the fact that the parameter λ depends on the noise level of the input data [1], different levels of Gaussian white noise are added to the LR input image to find appropriate value of λ that could give a common solution to this convex minimization problem. It is claimed in [9] that for Gaussian white noise with standard deviation σ, one typically sets $\lambda = T\sigma$ with $T \leq \sqrt{2\log_e P}$, where P is the dictionary size. In our experiments, λ smaller than 3.7062*σ could provide a solution. Experimental results show that the noisier the data the larger the value of λ should be, and best performance appears with λ having a value in the order of noise level σ.

c) Efficiency of Sparse Reconstruction Toolboxes

Various sparse reconstruction toolboxes are published to solve the L_1-L_2 norm minimization problem using convex optimization algorithms. For the readers' convenience, Table 3 lists the performance (i.e. computational accuracy and speed) of four popular sparse reconstruction toolboxes, i.e. SparseLab, l1_ls, YALL1and CVX. It is obvious that the four toolboxes share the same degree of reconstructed accuracy, while the SparseLab has significantly higher computational speed due to its parallel processing feature.

4. CONCLUSION

In this paper, the proposed SparseFI algorithm for pan-sharpening is validated using UltraCam and WorldView-2 data by comparing to other conventional pan-sharpening methods. The superior performance of SparseFI algorithm has been demonstrated by statistic assessment. SparseFI outperforms the other algorithms in most of the assessment, and especially in minimizing the spectral distortion. The analysis of dependency on the regularization parameter indicates that optimal λ has a value in the order of noise level σ. From the investigation of assessment the most popular sparse reconstruction toolboxes, SparseLab is much more computationally efficient while providing comparable reconstruction accuracy.

REFERENCES

[1] X. Zhu, X. Wang, R. Bamler, "Compressive Sensing for Image Fusion – with Application to Pan-sharpening", In: Proceedings of IGARSS Conference, 2011

[2] T. Tu, S. Su, H. Shyn and P. Huang, "A new look at IHS-like image fusion methods, Information Fusion", Vol. 2, pp. 177-186, 2001.

[3] V. P. Shah and N. H. Younan, "An efficient pan-sharpening method via a combined adaptive PCA approach and contourlets", IEEE Transactions of Geoscience and Remote Sensing, Vol. 46, No. 5, 2008.

[4] Y. Zhang, "Problems in the fusion of commercial high-resolution satellite images as well as Landsat-7 images and initial solutions." International Archives Of Photogrammetry Remote Sensing And Spatial Information Sciences, Vol. 34, Part 4, pp. 587-592, 2002.

[5] M. Moeller, T. Wittman and A. L. Bertozzi, "Variation wavelet pan-sharpening", IEEE Transactions of Geoscience and Remote Sensing, vol. 08, No.8, 2008

[6] J. Ender, 2010. On compressive sensing applied to radar. Signal Processing: Special Section on Statistical Signal & Array Processing 90: 1402–1414

[7] X. Zhu, R. Bamler, Tomographic SAR Inversion by L1 Norm Regularization – The Compressive Sensing Approach, IEEE Transactions on Geoscience and Remote Sensing, 48(10), pp. 3839-3846.

[8] J. Yang, J. Wright, T. Huang and Y. Ma, *Image super-resolution via sparse representation*, IEEE Trans. on Image Processing, Vol. 19, No. 11, pp. 2861-2873, 2010.

[9] S. Mallat, A wavelet tour of signal processing, Third Edition, Academic Press, Elsevier's Science & Technology Rights Department, Oxford, UK, pp. 664-665, 2009.

APPENDIX

Table 1.Quality metrics for UltraCam data (pan image simulated with 2.7% model error)

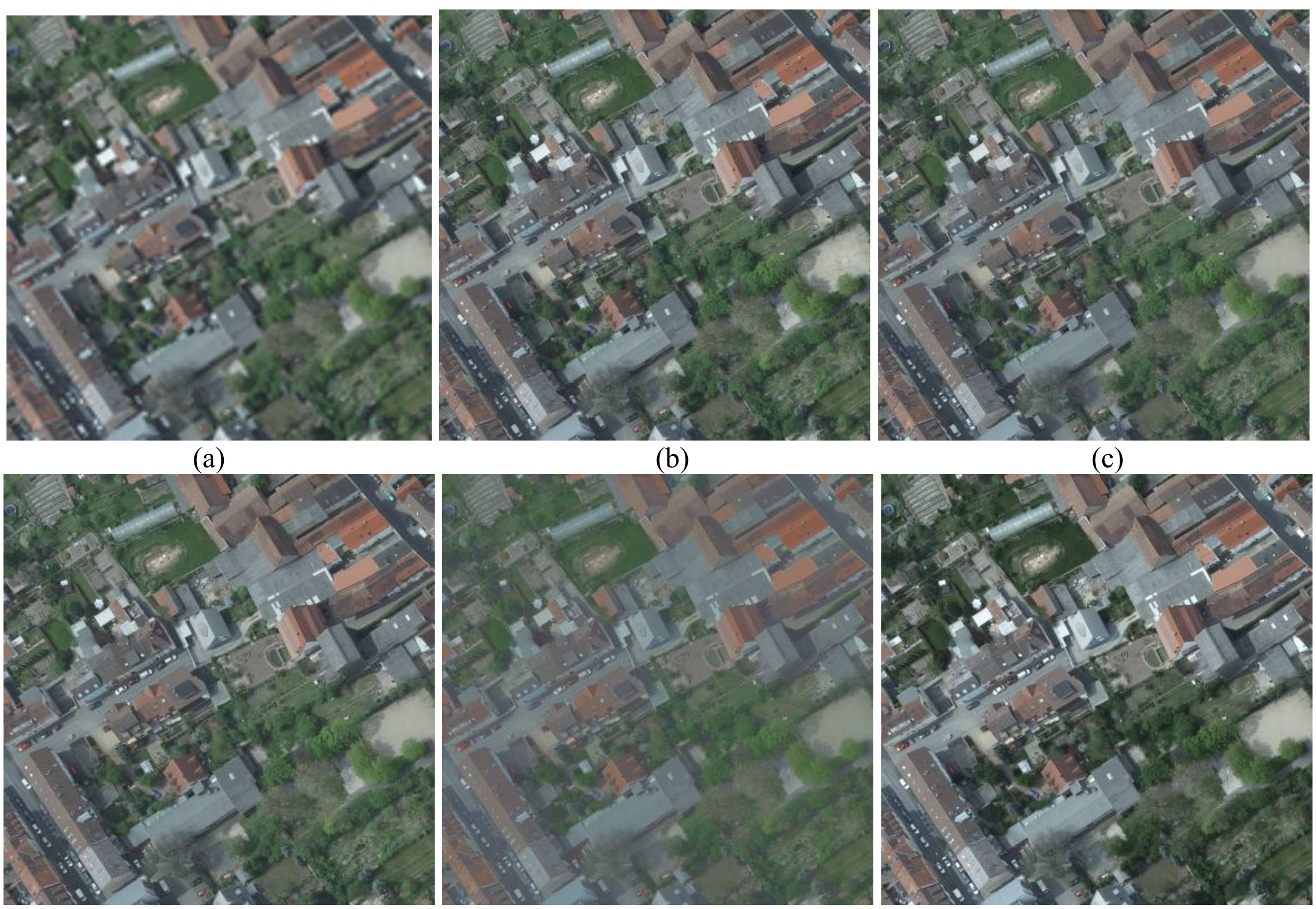
	RMSE	*P*	D	UIQI	Average Gradient	ERGAS
Optimum Values	0	1	0	1	+∞	0
IHS	4.4063	**0.9978**	3.4923	0.9918	5.3983	0.6297
Adaptive IHS	5.0060	0.9945	3.6287	0.9894	5.7153	0.7164
PCA	17.1850	0.9599	13.4960	0.8309	3.1857	2.4491
Brovey	9.3757	0.9782	7.9847	0.9709	**5.9233**	1.3420
SparseFI	**3.7080**	0.9954	**2.5903**	**0.9945**	5.5767	**0.5319**

Table 2. Quality metrics for WorldView-2 (Test site: Roma)

	RMSE	*P*	D	UIQI	Average Gradient	ERGAS
Optimal value	0	1	0	1	$+\infty$	0
IHS	11.4950	0.8157	7.4077	0.7983	5.9847	2.8974
Adaptive IHS	10.1623	0.8679	6.4243	0.8424	4.9600	2.5813
PCA	13.5273	0.8315	9.7280	0.6437	3.5163	3.4632
Brovey	29.0653	0.8163	26.1483	0.6335	5.2290	13.9439
SparseFI	**9.5433**	**0.8826**	**5.9840**	**0.8796**	**5.9903**	**2.4142**

Table 3. Quality metrics for different sparse reconstruction toolboxes

	RMSE	CC	D	UIQI	Average Gradient	ERGAS	Time (sec)
Optimal Values	0	1	0	1	$+\infty$	0	0
SparseLab	2.8976	0.9978	1.9385	0.9975	5.7926	0.3759	**35.95**
l1_ls	**2.8603**	0.9978	**1.9164**	0.9976	5.8104	**0.3712**	867.97
YALL1	2.8680	0.9978	1.9199	0.9976	5.8036	0.3722	603.79
CVX	2.9315	**0.9979**	2.0159	**0.9974**	**5.7579**	0.3791	744.86



(a) (b) (c)

(d) (e) (f)

Figure 1. (a) LR multispectral image with a down-sampling factor of 10; HR multichannel image reconstructed by SparseFI (b), IHS method (c), adaptive IHS method (d), PCA method (e) and Brovey transform method (f)