

# A Dictionary-Based Image Fusion for Integration of SAR and Optical Images

Meng Yang<sup>1, 2, \*</sup> and Gong Zhang<sup>2</sup>

**Abstract**—In this letter, a new image fusion methodology for integration of SAR and optical images using combined dictionary is proposed. The approach taken is based on sparse and redundant representations by employing a combined dictionary consisting of wavelets, shearlets and discrete cosine transform (DCT). Wavelets and shearlets provide pointlike and curvelike structures for the optical image, and DCT are taken as obtaining the best performance on SAR image. The experimental results demonstrate feasibility and effectiveness of the method.

## 1. INTRODUCTION

A SAR imagery is primarily determined by the dielectric and geometric properties of an object, and the transmit/receive configuration of the SAR sensor. An optical imagery is primarily determined by the material properties of objects, the illumination conditions of the scene, and the sensor perspective. SAR image has abundant texture and structural information while the optical image is based on spectral information which has both very good spatial and spectral resolutions. Image fusion will bring together complementary information contained in SAR and Optical images. Such fused images should be more useful for further image processing tasks such as image segmentation, object identification, and regional change detection [1].

With characteristics of localization and multi-resolution, wavelet has been widely used in image processing. However, wavelet transform can only characterize the trait and location of point singularity. It is not very effective in characterizing the high-dimensional geometrical structures, such as edges and textures in images. An affine-like system — shearlets — are designed to efficiently represent anisotropic functions at various scales, locations and orientations, in particular, curves in images [2]. A combination of wavelets and shearlets for image representation can benefit from the advantages of each transformation.

Designing dictionaries for the image representation can be done by either adaptive learning methods, or selecting pre-specified dictionaries. Both these techniques have been extensively studied in recent years, and some progresses have been achieved in this field. However, dictionary design for image representations is still an open question. In this letter, the fusion approach taken is based on over-complete dictionary combined by selecting pre-specified transforms, which can reduce the computation complexity compared to those of adaptive learning dictionary.

## 2. PROPOSED ALGORITHM

Suppose that two source images, SAR and RGB color images, have already been accurately registered.

The first step of the proposed method is filtering the source SAR image using the redundant DCT dictionary [3]. Let  $X$  and  $\tilde{X}$  denote the source SAR image and the despeckled SAR image, respectively.

---

*Received 18 August 2014, Accepted 29 September 2014, Scheduled 6 October 2014*

\* Corresponding author: Meng Yang (yangmeng372901@163.com).

<sup>1</sup> College of Communication Engineering, Hangzhou Dianzi University, Hangzhou 310018, China. <sup>2</sup> Key Laboratory of Radar Imaging and Microwave Photonics, Nanjing University of Aeronautics and Astronautics, Ministry of Education, Nanjing 210016, China.

Using the redundant DCT dictionary  $\psi_0$ , the despeckled image  $\tilde{X}$  can be obtained according to the sparse approximation by solving the following minimization problem:

$$\tilde{X} = \arg \min_X \|\psi_0^T X\|_1 \quad \text{subject to} \quad \|X - \tilde{X}\|_2 < \varepsilon \quad (1)$$

The second stage of the proposed method is separating source optical image into pointlike and curvelike parts. First of all, we convert the source optical image from RGB color space into YUV color space, which has components representing luminance  $Y$ , saturation  $U$ , and hue  $V$ . Next we separate the luminance  $Y$  into pointlike and curvelike components by employing a combined dictionary, which consists of wavelets and shearlets based on multi-scale decompositions. Let  $\psi_1$  and  $\psi_2$  be an orthonormal basis of wavelets and a tight frame of shearlets, respectively. Then, for scales  $i$ , we address the following minimization problem:

$$(\tilde{W}_i, \tilde{S}_i) = \arg \min_{W_i, S_i} \|\psi_1^T W_i\|_1 + \|\psi_2^T S_i\|_1 \quad \text{subject to} \quad \left\| Y - \sum_i (W_i + S_i) \right\|_2 < \varepsilon \quad (2)$$

where,  $\psi_1^T W_i$  are the wavelet coefficients of the signals  $W_i$ , which capture the energy in the pointlike component, and  $\psi_2^T S_i$  are the shearlet coefficients of the signals  $S_i$ , which capture the energy in the curvelike component. We notice that the frequency distribution of pointlike and curvelike of components is highly concentrated on the high frequencies — scaling subbands of large scales  $i$ . It is further noted that the  $\ell_1$  norm in (2) is placed on the analysis rather than the synthesis coefficients to avoid numerical instabilities and high computational complexity. In [4], an efficient algorithm is proposed to solve (2) for  $W_i$  and  $S_i$ .

The next step of the proposed method is the fusion of the SAR image and optical image via the integration of amplitude component  $\tilde{X}$ , and luminance components  $\tilde{W}_i$  and  $\tilde{S}_i$ :

$$F = \tilde{X} + \lambda \sum_i (\tilde{W}_i + \tilde{S}_i) \quad (3)$$

where,  $\lambda$  is a real number, or a real matrix, which can be estimated by optimization method according to the actual application background. In this letter, we assume for simplicity that  $\lambda = 1$ .

Since the source optical image and fusion image can be assumed to have similar saturation and hue for simplicity, the  $U$  and  $V$  components from source optical image can be substituted for the  $U$  and  $V$  components in the fused image respectively. In the YUV color space, the fused image has three components: luminance  $F$ , saturation  $U$ , and hue  $V$ . Finally, we convert the fused image from YUV color space into RGB color space.

### 3. RESULTS AND DISCUSSION

In this section, we conducted experiments to validate the effectiveness of the proposed method. As shown in Figure 1, two accurately registered SAR and optical image pairs are used for evaluation. Figure 1 shows some qualitative results for the fusion of the SAR image and optical image. Table 1 shows the fusion indexes to validate the effectiveness of the proposed method. The experiment results show a good performance, which can be illustrated by three objective quality criteria: standard deviation (STD) [5], entropy index (EI) and contrast index (CI). CI is defined as follows:

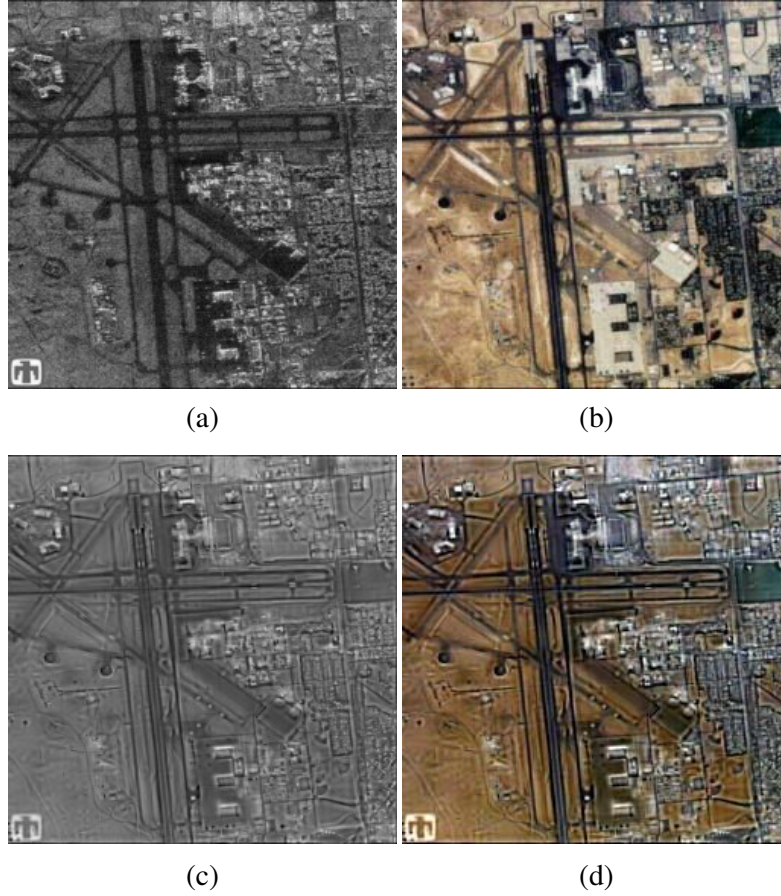
$$CI = \frac{\sigma^2}{\sqrt[4]{M_f}} \quad (4)$$

where  $\sigma^2$  is the variance of the image and  $M_f$  the fourth-order moment of the image. If the CI value becomes higher after fusion, it indicates that the information quality increases with contrast enhancement, and the fusion performances are improved. The CI in a RGB color image is given by

$$CI = (CI_R + CI_G + CI_B)/3 \quad (5)$$

where  $R$ ,  $G$ , and  $B$  denote the three color components respectively, and  $CI_R$  denotes the contrast in component  $R$ .

Figure 1 and Table 1 show that the proposed method has the advantage of incorporating abundant texture, structural, and spectral information. Automatic SAR image analysis may be further facilitated by incorporating high-resolution optical imagery.



**Figure 1.** (a) Source SAR imagery. (b) Source optical imagery. (c) Luminance component of fusion imagery. (d) Fused imagery.

**Table 1.** Objective measurement with three indexes.

Indexes	Figure 1(a)	Figure 1(b)	Figure 1(c)	Figure 1(d)
STD	<b>33.1399</b>	51.6073	35.9999	<b>42.6522</b>
EI	<b>7.0102</b>	7.6267	7.1428	<b>7.2565</b>
CI	<b>23.0592</b>	41.9175	25.1748	<b>30.8219</b>

#### 4. CONCLUSION

This letter proposes an efficient method for fusing SAR and optical images based on sparse approximation techniques, which combines the advantages of wavelets, shearlets, and redundant DCT dictionary. Experimental results show that the proposed method can efficiently preserve the fused image's spectral information, while increasing the spatial clarity and the potential of texture and structural analysis by SAR and optical images. Future work will focus on interpretation using fused images enhanced by incorporating the optical images' features into SAR images.

#### ACKNOWLEDGMENT

This work was supported in part by the Key Laboratory of Radar Imaging and Microwave Photonics (Nanjing University of Aeronautics and Astronautics), Ministry of Education under Grant RIMP-

2013004, and in part by the Project of Department of Education of Zhejiang Province under Grant Y201329881.

## REFERENCES

1. Wang, T. L. and Y. Q. Jin, "Postearthquake building damage assessment using multi-mutual information from pre-event optical image and postevent SAR image," *IEEE Geosci. Remote Sens. Lett.*, Vol. 9, No. 3, 452456, May 2012.
2. Kong, W. W., "Multi-sensor image fusion based on NSST domain I<sup>2</sup>CM," *Electron. Lett.*, Vol. 49, No. 13, 802–803, Jun. 2013.
3. Elad M. and M. Aharon, "Image denoising via sparse and redundant representations over learned dictionaries," *IEEE Trans. Image Processing*, Vol. 15, No. 12, 3736–3745, Dec. 2006.
4. Kutyniok, G. and W. Q. Lim, "Image separation using wavelets and shearlets," 2010, [http://www.shearlab.org/index\\_publications.html](http://www.shearlab.org/index_publications.html).
5. Guo, R., L. Zhang, M. Xing, and J. Li, "Polarimetric SAR image fusion using nonnegative matrix factorisation and improved-RGB model," *Electron. Lett.*, Vol. 46, No. 20, 3736–3745, Sep. 2010.