Journal of Engineering Sciences
Vol 10, Issue 12, DEC/2019
ISSN NO:0377-9254

APPLICATION OF MULTI-SENSOR IMAGE FUSION OF INTERNET OF THINGS IN IMAGE PROCESSING

T. SIVA PARVATHI[1], T. MAHABOOB RASOOL[2]
[1]PG Student, Dept of ECE(DECS), BCETFW, Kadapa, AP, India.
[2]Associate Professor, Dept of ECE, BCETFW, Kadapa, AP, India.

ABSTRACT- The perception layer of Internet of Things (IOT) consists of various sensors. It is the source of the IOT to identify objects and collect information. Information fusion collected from multi-sensor has been widely used in various fields, such as intelligent industry, intelligent agriculture, intelligent transportation, intelligent environmental protection etc. In this paper, multi-sensor image fusion, Multispectral (MS) and Panchromatic (PAN) images, is studied, and the fused images are used in target detection, recognition and classification and so on. However, traditional methods based on injection model generally consider the MS images as a whole to compute the spectral weights. They ignore the local information of MS images and produce some spectral distortions because for different objects, the spectral response will be different. Therefore, we propose a novel multi-sensor image fusion based on application layer of IOT (IFIOT) to preserve the spectral information of MS images. In this method, local homogeneous areas are found first by superpixel segmentation. Due to good properties of superpixel, the homogeneous areas are uniform and contain only one kind of object. Then, we estimate the spectral weights for different bands on the homogeneous area. The injection gain has an important influence on fusion results. Therefore, we adaptively compute the gain coefficients by minimizing the error between spectral degraded MS and PAN images. Finally, after the injection of spatial details obtaining from PAN image, fused images are produced. Experimental results reveal that IFIOT method can give good fusion results and the spectral information is preserved well.

I. INTRODUCTION

WITH the development and deployment of high-resolution sensors, IKONOS provides both multispectral (MS) and panchromatic (Pan) data with spatial resolutions of 4 and 1 m, respectively. The MS images have four wavelength bands; blue [0.45–0.52 m (B)], green [0.52–0.60 m (G)], red [0.63–0.0.69 m (R)], and near infrared [0.76–0.90 m (NIR)]. Clearly visible being individual trees, automobiles, road networks, and houses, the IKONOS images allow for a more accurate understanding of phenomena on the ground. To take the advantage of the high spatial information content in the Pan image and of the essential spectral information in MS images, image fusion is often an efficient and economical means to produce MS images with high spatial resolution. To date, various image fusion methods have been proposed in the literature [1]–[7]. In our early work [6], the intensity-hue–saturation (IHS) transform, Brovey transform (BT), principal component analysis (PCA), and wavelet transform (WT) have been mutually compared in spatial and spectral features based on a common IHS-like framework. As a result, only the WT method can be regarded as the technique of high-pass filtering by improving the spatial resolution but distorting the color composite [2]. The other techniques may also change the mean of fused bands because they inject not only high-pass but also low-pass components. For practical applications, WT methods are not efficient for IKONOS image fusion due to the lack of translation invariance in multiresolution analysis and inappropriate selection of filters. With the development of wireless sensor network with computing ability and communication ability, smart visual Internet of Things (IOT) has been widely used in various fields [1-2]. The IOT architecture includes perception, network and application layers. Perception layer consists of different sensors, including temperature and humidity sensor, RFID tag and reader, camera, infrared ray, GPS etc. A large number of sensors of various types are deployed on the IOT. Information content obtained by different sensors can satisfy the requirement of collection and compression of multimedia information like images, audios and videos in practical applications. Network layer is the core of IOT, and it has different networks, such as internet, network and cloud computing platform etc. The main task of the network layer is the

processing and transmission information. Application layer is an interface of users and IOT, which meets the users' needs to realize the smart application of IOT. Remote sensing is a non-contact remote detection technology that monitor the earth's surface by installing remote sensing monitoring instruments on satellites. At present, with the rise and development of IOT, the application of remote sensing monitoring and IOT technology has also presented a new development trend, such as target detection, recognition and classification [3-5] etc. In recent years, many satellites are launched into space. At the same time, a large amount of remote sensing data are obtained by these satellites, such as multispectral (MS) images and panchromatic (PAN) image. However, the limitation of spectral resolution and spatial resolution always exists because of remote sensing technology.

II. IHS FUSION AND SPECTRAL DISTORTION

The IHS transform is widely used as an image fusion technique to exploit the complementary nature of multisensor image data. IHS fusion uses an RGB image consisting of distinct bands and transforms them into the IHS space. The intensity component in the IHS space is replaced by the Pan image with high spatial resolution and then transformed back into the original RGB space with the previous hue and saturation components. The IHS fusion for each pixel can be formulated by the following procedure [1], [2], [6].

Step 1) Upsample (resize) the low spatial resolution RGB image to the size of the high spatial resolution Pan image.

Step 2)

$$\begin{bmatrix} \mathrm{I} \\ v1 \\ v2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ -\frac{\sqrt{2}}{6} & -\frac{\sqrt{2}}{6} & \frac{2\sqrt{2}}{6} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 \end{bmatrix} \begin{bmatrix} \mathrm{R} \\ \mathrm{G} \\ \mathrm{B} \end{bmatrix}.$$

Step 3) The intensity image I is replaced by Pan image.

Step 4)

$$\begin{bmatrix} \mathrm{R}' \\ \mathrm{G}' \\ \mathrm{B}' \end{bmatrix} = \begin{bmatrix} 1 & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 1 & -\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ 1 & \sqrt{2} & 0 \end{bmatrix} \begin{bmatrix} \mathrm{Pan} \\ v1 \\ v2 \end{bmatrix}$$

To understand the influence of spectral response on the fusion of IKONOS images, the relative spectral responses [8] depicted in Fig. 1 are investigated in detail. Ideally, the RGB bands should fall just within the spectral range of the panchromatic band. From Fig. 1, however, it appears that the green and blue bands overlap substantially, and the blue band mostly falls outside the 3–dB cutoff of the Pan band. Furthermore, the response of the Pan band is extended beyond the NIR band. Obviously, the color distortion problem in IHS fusion results from such mismatches, in that P and I are not spectrally similar. On the other hand, vegetation appears of relatively high reflectance in NIR and Pan bands, while of low reflectance in RGB bands. Since the effect of the NIR band is not included in I for the vegetation areas, the DN values in I are much smaller than those in Pan. This will cause a large value, which results in significant color distortion in green vegetation regions of the fused image. To reduce the color distortion that originated from the fusion process, it is essential to lower the value, i.e., is to include the response of NIR band into I.

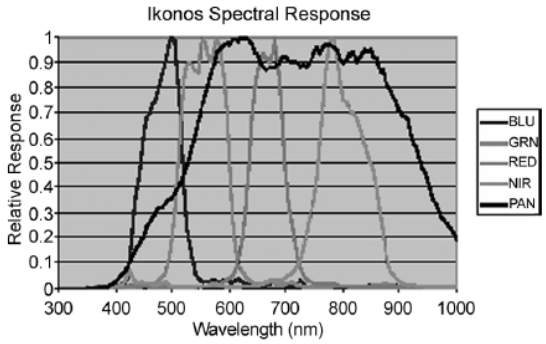

Fig. 1. IKONOS relative spectral responses.

For doing so, 92 IKONOS images, covering different areas, are used to explore the best values. For simplification, based on the fact that the blue band is farther from the Pan band than the green band in Fig. 1, we assume that In this work, we use the correlation coefficients between the original MS imagery (including R, G, B, and NIR bands) and the fused image as an index to determine the values. The average correlation coefficients of 92 IKONOS images are listed in Table I. In this table, is decreased from 0.9 to 0.6, and is increased from 0.1 to 0.4; each step is changed by 0.05. According to experimental results, the best weighting parameters of and for G and B bands are 0.75 and 0.25, respectively. Those values are suitable to represent the average reflectance of spectral response on the 92 IKONOS images.

TABLE I
AVERAGE CORRELATION COEFFICIENTS OF 92 IKONOS MS IMAGES BETWEEN RESAMPLED AND FUSED BANDS, VARYING WITH SPECTRAL WEIGHTS

a	0.9	0.85	0.8	0.75	0.7	0.65	0.6
b	0.1	0.15	0.2	0.25	0.3	0.35	0.4
CCs	0.629	0.768	0.835	0.837	0.829	0.815	0.803

III. MULTI-SENSOR IMAGE FUSION BASED ON APPLICATION LAYER OF IOT

We first describe the framework of injection model [33] for image fusion task, and then describe the proposed method based on application layer of IOT, which the core idea is superpixel and adaptive gain in detail.

A. Injection Model

We use to stand for MS images. is each band of MS images. B is the number of bands of MS images. denotes PAN image. and are the horizontal and vertical size of PAN image. is the spatial resolution ratio between MS and PAN images. For MS and PAN images fusion, we consider the case that MS images contain four bands, since the number of bands is 4 for most satellites. According to the injection model theory, the formulation can be written as: r c rNrNR □ □ M □ □ 1,..., b bB□ M r c NNR □ □ P rN c N r

$$\hat{\mathbf{M}}_b = \tilde{\mathbf{M}}_b + g_b \mathbf{D}_b$$

In (1), b **M** is the resampled band of MS images, and the size of b**M** is the same size of PAN image. b**M** denotes the fused band. b g is the corresponding gain coefficient for each band, which is decided by the spectral and spatial information jointly. b **D** is the spatial details to be injected, which is also named as high frequency information. Then, the injection model can be written as:

$$\hat{\mathbf{M}}_b = \tilde{\mathbf{M}}_b + g_b \left(\mathbf{P} - \sum_{b=1}^{B} w_b \tilde{\mathbf{M}}_b \right)$$

where is the corresponding spectral weight of each band. By combining the bands in MS images with different weights, a simulated intensity image is obtained. Then, the spatial details can be produced by the difference of PAN and simulated intensity images. For different band, the injection gain will be different. Generally, MS and PAN images are all considered to decide the gain coefficients. For instance, spectral weights are computed by least square in the minimum mean-square-error sense in [34]. However, the weights are computed for the whole image and ignore the local consistency. Because for different local areas contains different objects, the spectral weights will be different. Therefore, some spectral distortions maybe can be seen from the fusion results. bw bD b g

B. Multi-sensor Image Fusion Based on Application Layer of IOT

It is obvious that using a fixed spectral weight is not feasible for a whole image. For different homogeneous areas, the spectral weights will have great differences. Therefore, we first have to find the homogeneous area which contains one kind of object. There are some methods to be used to find proper areas. For example, some methods find the areas by clustering with intensity and local standard deviation [35]. However, the method maybe produce some spectral distortions due to the uncertainty of standard deviation. On the contrary, as a segmentation technique, superpixel has been developed a lot and can find uniform area effectively. Therefore, in our method, superpixel is used to find the homogeneous areas. In [32], a superpixel method based on entropy rate is proposed which presented a new graph construction method for images and produce more natural segmentation results. So, we adopt the method to segment PAN image into many homogeneous areas. This objective function of the superpixel method is composed of two parts. One is entropy rate of a random walk on a graph. The other is a balancing term. They can be efficiently implemented and give the state of the art segmentation
results. The areas in PAN image can be denoted as □ □ 1, 2,..., k kK□ **P** after superpixel segmentation. K is the total number of superpixels in PAN image and k is the k-th superpixel in PAN image. Then, the corresponding areas of MS images can be find using PAN image according to the pixel locations in PAN image. We use k b **M** to denote the superpixel in each band of b**M** . After finding the homogeneous areas, we calculate the spectral weights from the resampled MS images **M** and the spatial degraded PAN image **P** . And **P** is produced by the operation with the low-pass filter. The corresponding superpixel of **P** is k **P** . Then, for the k-th superpixel, the spectral weights of MS images can be calculated by minimizing (3).

$$\min \left\| \tilde{\mathbf{P}}^k - \sum_{b=1}^{B} w_b^k \tilde{\mathbf{M}}_b^k \right\|_2^2$$

where and are rearranged a vector. Obviously, the spectral weights can be easily calculated by least

square method. stands for the spectral weight on each band for the k-th superpixel. Then, we inject the spatial details into the resampled MS images by (4). k P kb M bw k b w

$$\hat{\mathbf{M}}_b^k = \tilde{\mathbf{M}}_b^k + g_b^k \left(\mathbf{P}^k - \sum_{b=1}^{B} w_b^k \tilde{\mathbf{M}}_b^k \right)$$

Obviously, gain coefficient is important in the image fusion process. Proper gain coefficients can preserve the spectral information well. As we all know, PAN image can be considered as the degraded result of HMS images in spectral domain. So, when obtain an HMS images, we hope the difference between PAN and the spectral HMS is minimum. Then, the assumption can be written as: k b g

$$\min \left\| \mathbf{P}^k - \sum_{b=1}^{B} w_b^k \left(\tilde{\mathbf{M}}_b^k + g_b^k \left(\mathbf{P}^k - \sum_{b=1}^{B} w_b^k \tilde{\mathbf{M}}_b^k \right) \right) \right\|_2^2$$

Therefore, after estimating the gain coefficients adaptively, the fused images can be produced by (4). The main steps of IFIOT method are listed as follows.

Algorithm: Multi-sensor Image Fusion Based on Application Layer of IOT (IFIOT)

Input: PAN image $\mathbf{P}$ and MS images $\mathbf{M}$

Step 1: Produce the resampled MS image $\tilde{\mathbf{M}}$

Step 2: Segment PAN image into superpixels $\mathbf{P}^k \, (k = 1, 2, \ldots, K)$

Step 3: Obtain corresponding superpixels of resampled MS image $\tilde{\mathbf{M}}_b^k \, (k = 1, 2, \ldots, K)$

Step 4: for $k = 1{:}K$

Calculate spectral weight w_b^k by (3)

Compute gain coefficient g_b^k by (7)

Produce the fused superpixels $\hat{\mathbf{M}}_b^k$ by (4)

end

Step 5: Put the fused superpixels into orginal locations

Output: HMS images $\hat{\mathbf{M}}_b$

IV RESULTS

Comparision table:

Metric	EXISTING METHOD	PROPOSED
RMSE	27.54	16.43
PSNR	20.13	34.15

REFERENCES

[1] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," Comp. Networks, vol. 54, no. 15, pp. 2787-2805, Oct. 2010.

[2] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A Vision, Architectural Elements, and Future Directions," Future Gener. Comp. Syst., vol. 29, no. 7, pp. 1645- 1660, Sep. 2012.

[3] Y. LI, X. Sun, H. Wang, H. Sun, and X. Li, "Automatic target detection in high-resolution remote sensing images using a contour-based spatial model," IEEE Geosci. Remote Sens. Lett., vol. 9, no. 5, pp. 886-890, Sep. 2012.

[4] L. Zhang, L. Zhang, D. Tao, and X. Huang, "A multifeature tensor for remote-sensing target recognition," IEEE Geosci. Remote Sens. Lett., vol. 8, no. 2, pp. 374-378, Mar. 2011.

[5] A. Samat, P. Gamba, S. Liu, P. Du, and J. Abuduwaili, "Jointly informative and manifold structure representative sampling based active learning for remote sensing image classification," IEEE Trans. Geosci. Remote Sens., vol. 54, no. 11, pp. 6803-3817, Nov. 2016

[6] C. Psjr, S. C. Sides, and J. A. Anderson, "Comparison of three different methods to merge multiresolution and multispectral data: landsat TM and SPOT panchromatic," Photogramm. Eng. Remote Sens., vol. 57, no. 3, pp. 265-303, Mar., 1991.

[7] W. J. Carper, T. M. Lillesand, and R. W. Kiefer, "The use of intensity-hue-saturation transform for merging spot panchromatic and multispectral," Photogramm. Eng. Remote Sens., vol. 56, no. 4, pp. 459-467, Apr. 1990.

[8] C. A. Laben and B. V. Brower, "Process for enhancing the spatial resolution of multispectral imagery using pan-sharpening." U.S. Patent 6011875, 4 January 2000, Eastman Kodak Company

[9] T. Tu, P. Huang, C. Hung, and C. Chang, "A fast intensity-hue-saturation fusion technique with spectral adjustment for IKONOS imagery," IEEE

Geosci. Remote Sens. Lett., vol. 1, no. 4, pp. 309-312, Oct. 2004.
[10] B. Aiazzi, S. Baronti, and M. Selva, "Improving component substitution pansharpening through multivariate regression of MS+PAN data," IEEE Trans. Geosci. Remote Sens., vol. 45, no. 10, pp. 3230-3239, Oct. 2007.
[11] Z. Wang, D. Ziou, C. Armenakis, D. Li, and Q. Li, "A comparative analysis of image fusion methods," IEEE Trans. Geosci. Remote Sens., vol. 43, no. 6, pp. 1391-1402, Jun. 2005
[12] S. Yang, M. Wang, and L. Jiao, "Fusion of multispectral and panchromatic images based on support value transform and adaptive principal component analysis," Inf. Fusion, vol.3, pp. 177-184, Mar. 2012.