Classification of Fused SAR/EO Images Using Transformation of Fusion Classification Class Label

Chul-Soo Ye

Department of Ubiquitous IT, Far East University

Abstract : Strong backscattering features from high-resolution Synthetic Aperture Rader (SAR) image provide useful information to analyze earth surface characteristics such as man-made objects in urban areas. The SAR image has, however, some limitations on description of detail information in urban areas compared to optical images. In this paper, we propose a new classification method using a fused SAR and Electro-Optical (EO) image, which provides more informative classification result than that of a single-sensor SAR image classification. The experimental results showed that the proposed method achieved successful results in combination of the SAR image classification and EO image characteristics.

Key Words : SAR-EO Image Fusion, Maximum Likelihood Classification, Initial Classification Class Label, Fusion Classification Class Label, Final Fusion Classification Label

1. Introduction

Multi-sensor image fusion provides additional information and improved analysis on target objects. Image fusion basically combines various information into a single fused information, which can offer a new way to analyze the target object. A variety of image fusion methods have been proposed (Li *et al*, 2003; Long and Gaungfang, 2007; Petrovic and Xydeas, 2004; Piella, 2003). Image fusion methods using SAR and EO images were also proposed in order to analyze urban areas (Fatone *et al*, 2001; Garzelli, 2002; Ye, 2009; Ye, 2010). Multiple fused images

were obtained using SAR and EO images by a wavelet-based fusion of SAR and EO images using gradient and variance (Ye, 2010). This method can control the amount of each sensor image inserted into the fused image. This means we can obtain various types of fused images from SAR and EO images and also apply these fused images to some application fields such as classification, pattern recognition and etc.

In this paper, we propose the rules combining the multiple classification results of the fused images obtained from SAR and EO images into one classification result (Fig. 1). The advantage of the proposed method is that a new information (i.e.,

Received November 9, 2012; Revised December 14, 2012; Accepted December 17, 2012.

[†] Corresponding Author: Chul-Soo Ye (csye@kdu.ac.kr)

This is an Open-Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (<http://creativecommons.org/licenses/by-nc/3.0>) which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

Fig. 1. Overall procedure of the proposed algorithm.

homogeneous intensity property) from EO image is inserted into the classification result of the fused image. We can obtain more informative land use classification result of SAR image, which is difficult to be obtained from SAR image alone. First, we create multiple fused images from SAR and EO images and then classify the pixels in each fused image into some class labels using Maximum Likelihood Classification (MLC) method. We combine the classified images into Fusion Classification Class Label (FCCL) using some combination rules. We also classify the SAR image into some class labels (Initial Classification Class Label, ICCL) using MLC method. The Final Fusion Classification Label (FFCL) is obtained by combining ICCL and FCCL.

2. Methodology

1) Maximum Likelihood Classification (MLC)

Maximum Likelihood Classification is a popular supervised classification method, where sample pixels are chosen to make training samples and then each pixel in the entire image is classified into the corresponding class based on the maximum likelihood. Denoting the number of the band images by N , the feature vector extracted from band image is defined as follows:

$$\mathbf{x} = [x_1, x_2, \dots, x_N] \quad (1)$$

After selecting the training samples, the mean vector $\mathbf{m}_k$ and the covariance matrix $\mathbf{C}_k$ are computed as follows:

$$\mathbf{m}_k = \frac{1}{M} \sum_{i=1}^M \mathbf{x}_i^k \quad (2)$$

$$\mathbf{C}_k = \frac{1}{M} \sum_{i=1}^M (\mathbf{x}_i^k - \mathbf{m}_k)(\mathbf{x}_i^k - \mathbf{m}_k)^T \quad (3)$$

where M is the total number of pixels in training set.

The probability of each class is computed as follows:

$$p(\mathbf{x}|\mathbf{v}_k) = \frac{1}{(2\pi)^{N/2} \sqrt{\det(\mathbf{C})}} \exp\left(-\frac{1}{2}(\mathbf{x} - \mathbf{m}_k)^T \mathbf{C}^{-1}(\mathbf{x} - \mathbf{m}_k)\right) \quad (4)$$

Finally we assign the class with maximum probability to the pixel as follows:

$$\mathbf{v}_k = \underset{\mathbf{v}_i}{\operatorname{argmax}} (p(\mathbf{x}|\mathbf{v}_i)p(\mathbf{v}_i)), (k, i = 1, 2, \dots, N_C) \quad (5)$$

2) Classification of SAR-EO fused image using MLC

Fused image $I_F(i, j)$ generated from SAR image $I_S(i, j)$ and EO image $I_O(i, j)$ is defined as follows:

$$I_k^F(i, j) = W_S(k) \cdot I_S(i, j) + W_O(k) \cdot I_O(i, j), \quad (6)$$

$$W_S(k) + W_O(k) = 1$$

where $W_S(k)$ and $W_O(k)$ are fusion weights for SAR image and EO image, respectively. The fusion weights are determined by using the gradient and variance based fusion method (Ye, 2010). This fusion method employs the ratio of pixel intensity of SAR image over EO image, gradient magnitude and intensity variance. If the intensity value of SAR image is stronger than that of EO image, the fused image accepts the intensity value of SAR image as its intensity value. Otherwise the intensity value of the

Fig. 2 Fused images according to discrete weight parameters.

fused image is determined by a weighted sum of SAR and EO images.

The weight value has two factors of the gradient magnitudes of pixels and the intensity variances of pixels in a local area in the two images as follows:

$$W_S(k) = k \cdot f_s(G_S, G_O, \sigma_S, \sigma_O) \quad (7)$$

$$W_O(k) = (1 - k) \cdot f_s(G_S, G_O, \sigma_S, \sigma_O) \quad (8)$$

where G_S and G_O are gradient magnitudes of the pixels of SAR image and EO image, respectively, and σ_S and σ_O are standard deviations of the intensity values of the pixels in a local area in SAR image and EO image, respectively. The parameter k is a weight value controlled according to fusion purpose.

By controlling the parameter k we can generate various fused images. For the parameter range $0 < k < 1$, the discrete weight k_q is given by

$$k_q = \frac{1}{N} \cdot q, (q = 1, 2, \dots, N - 1) \quad (9)$$

For example, for $N = 10$, the discrete weight k_q has 9 weight values as follows:

$$k_q = \left\{ \frac{1}{10}, \frac{2}{10}, \frac{3}{10}, \frac{4}{10}, \frac{5}{10}, \frac{6}{10}, \frac{7}{10}, \frac{8}{10}, \frac{9}{10} \right\} \quad (10)$$

Consequently, when the discrete weight k_q is applied to equation (6), the fused image $I_F(i, j)$ is given by

$$I_{k_q}^F(i, j) = W_S(k_q) \cdot I_S(i, j) + W_O(k_q) \cdot I_O(i, j), \quad (11)$$

$$W_S(k_q) + W_O(k_q) = 1$$

Fig. 2 shows the relationship between the fused images and discrete weight parameters. We classify the fused image $I_{k_q}^F(i, j)$ by MLC method to generate the classified image $C_{k_q}^F(i, j)$ given by

$$C_{k_q}^F(i, j) = \{c_p | p = 1, 2, \dots, N_C\} \quad (12)$$

where N_C is the total number of classes and the element c_p is a class label assigned to each class. In order to determine whether the classified image $C_{k_q}^F(i, j)$ has class label c_p , class label detection function $N_{q,p}(i, j)$ is defined as follows:

$$N_{q,p}(i, j) = N_{k_q,p}(i, j) [C_{k_q}^F(i, j)] = \begin{cases} 1 & \text{if } C_{k_q}^F(i, j) = c_p \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

If the classified image $C_{k_q}^F(i, j)$ has class label c_p , the class label detection function is one, otherwise class label detection function is zero. The class label matrix element $C_p^T(i, j)$ is defined by

$$C_p^T(i, j) = \sum_{q=1}^{N-1} N_{q,p}(i, j) \quad (14)$$

The class label matrix element $C_p^T(i, j)$ represents the number of the classified images where the class label at (i, j) has c_p . Table 1 shows the relationship between the class label detection function $N_{q,p}(i, j)$ and class label matrix element $C_p^T(i, j)$. For example, for class label $p = 1$, if the classified image $C_1^F(i, j)$ has class label one, then the class label detection function $N_{1,1}(i, j)$ is one, otherwise $N_{1,1}(i, j)$ is zero. In this case, the class label matrix element $C_1^T(i, j)$ is

Table 1. The relationship between the class label detection function $N_{q,p}(i,j)$ and class label matrix element $C_p^T(i,j)$

Class	$C_1^F(i,j)$	$C_2^F(i,j)$	...	$C_{N-1}^F(i,j)$	$C_p^T(i,j)$
1	$N_{1,1}(i,j)$	$N_{2,1}(i,j)$	...	$N_{N-1,1}(i,j)$	$\sum_{q=1}^{N-1} N_{q,1}(i,j)$
2	$N_{1,2}(i,j)$	$N_{2,2}(i,j)$	...	$N_{N-1,2}(i,j)$	$\sum_{q=1}^{N-1} N_{q,2}(i,j)$
⋮		⋮			⋮
3	$N_{1,N_C}(i,j)$	$N_{2,N_C}(i,j)$	...	$N_{N-1,N_C}(i,j)$	$\sum_{q=1}^{N-1} N_{q,p}(i,j)$

(a)

(b)

Fig. 3. Sample images (a) high intensity pixels in EO image (b) corresponding area in SAR image.

given by

$$C_1^T(i,j) = \sum_{i=1}^{N-1} N_{q,1}(i,j) = N_{1,1}(i,j) + N_{2,1}(i,j) \quad (15)$$

This means the number of classified images where the class label at (i,j) has one. After computing the class label matrix element $C_p^T(i,j)$, the class label p_F , which we call Fusion Classification Class Label (FCCL), is defined as the class label of the maximum class label matrix element $C_p^T(i,j)$ as follows:

$$p_F = \operatorname{argmax}_p \{C_p^T(i,j)\} \quad (16)$$

3) Transformation of the Fusion Classification Class Label (FCCL)

A fused SAR-EO image has mixed characteristics of SAR and EO images. If the parameter approaches zero, the amount of the SAR signal in the fused SAR/EO image increases. On the other hand, if the parameter approaches one, the amount of the EO

signal in the fused SAR/EO image increases. If the intensity value of SAR image is weaker than that of EO image, the intensity value of the fused image is determined by a weighted sum of SAR and EO images. As shown in Fig. 3, those pixels that have high intensity value, low gradient magnitude and low variance are inserted to the fused image according to the fusion rules. In this case, the pixels with strong backscattering in SAR image and the high intensity pixels in homogeneous region in EO image will have same class in the fused image. Therefore we need to refer to the classification result of SAR image before we determine the final class of the fused image.

We define Initial Classification Class Label (ICCL) $C_p^R(i,j)$ obtained from classification of SAR image alone, Fusion Classification Class Label (FCCL) $C_p^M(i,j)$ and Final Fusion Classification Label (FFCL) $C_p^L(i,j)$ obtained from transformation

Table 2. Three classes for TerraSAR-X satellite image

Class	Intensity	Land use types
c_1^R	High intensity pixels	Strong backscattering objects
c_2^R	Middle intensity pixels	Forset, grass, farmland, etc.
c_3^R	Low intensity pixels	Shadow, Water

(a)

(b)

Fig. 4. Initial classification of TerraSAR-X satellite image (a) TerraSAR-X satellite image (b) Initial Classification Class Label (ICCL) image classified by MLC.

Table 3. Transformation of the Fusion Classification Class Label (FCCL) into the Final Fusion Classification Label (FFCL)

FCCL	FFCL	Conditions
c_1^M	$c_1^M \rightarrow c_1^L$	$C_p^R(i, j) \neq c_3^R$
	$c_2^M \rightarrow c_2^L$	$C_p^R(i, j) = c_2^R$
	$c_3^M \rightarrow c_3^L$	$C_p^R(i, j) = c_3^R$
c_2^M	$c_2^M \rightarrow c_2^L$	$C_p^R(i, j) \neq c_3^R$
		$C_p^R(i, j) = c_3^R \wedge C_2^T(i, j) > (N-1)/2$
c_3^M	$c_3^M \rightarrow c_3^L$	$C_p^R(i, j) = c_3^R$
c_1^M, c_2^M, c_3^M	$new\ label \rightarrow c_4^L$	$C_p^R(i, j) = c_3^R \wedge C_2^T(i, j) \leq (N-1)/2$

of the FCCL are, respectively, as follows :

$$C_p^R(i, j) = \{C_p^R | p = 1, 2, \dots, N_C\} \quad (17)$$

$$C_p^M(i, j) = \{C_p^M | p = 1, 2, \dots, N_C\} \quad (18)$$

$$C_p^L(i, j) = \{C_p^L | p = 1, 2, \dots, N_D\} \quad (19)$$

where N_C and N_D are the total number of the classes in ICCL and FCCL, respectively.

We assume that the total number of the classes in ICCL and FCCL for TerraSAR-X satellite image is three, respectively ($N_C = N_D = 3$). Table 2 shows the three classes for TerraSAR-X satellite image

according to the level of pixel intensity. The land use types of TerraSAR-X satellite image such as strong backscattering object, shadow and water are easily discriminated based on the intensity of pixels. On the other hand, the land use type belonging to middle level intensity is difficult to be classified into more detail classes. Fig. 4 shows TerraSAR-X satellite image and ICCL image classified by MLC. We assigned pixel intensities 230, 100 and 0 to the class label c_1^R , c_2^R and c_3^R in the class label image, respectively.

The FCCL is determined as the class label with

maximum class label matrix element and has three class labels c_1^M , c_2^M and c_3^M , while the FFCL has four class labels c_1^L , c_2^L , c_3^L and c_4^L . Table 3 shows the conditions for transformation of the FCCL into the FFCL.

(1) Transformation of FCCL C_1^M

If the initial classification class label (ICCL) $C_p^R(i, j)$ satisfies the condition $C_p^R(i, j) \neq c_3^R$, then the fusion classification class label (FCCL) c_1^M is assigned to the final fusion classification label (FFCL) c_1^L , that is, if the initial classification class label is not the class label (c_3^R) belonging to low intensity pixels, then we assign c_1^M to c_1^L . Although the fusion classification class label has the class label c_1^M , we assign c_2^M and c_3^M to c_2^L and c_3^L , respectively. This means that if a pixel that is not classified into c_1^R (that is, high intensity pixel) in initial classification class label image, we accept the classification result of the initial classification class label image (that is, $c_2^M = c_2^R$ and $c_3^M = c_3^R$) as the final fusion classification label c_2^L and c_3^L , respectively. This condition is necessary for the pixels that have high intensity value, low gradient magnitude and low variance in the EO image, while the corresponding pixels in the SAR image do not have strong backscattering.

(2) Transformation of FCCL C_2^M

If the initial classification class label $C_p^R(i, j)$ satisfies the condition $C_p^R(i, j) \neq c_3^R$, then the fusion classification class label c_2^M is assigned to the final fusion classification label c_2^L . According to the second condition $C_p^R(i, j) = c_3^R \wedge C_2^T(i, j) > (N - 1)/2$, if the initial classification class label $C_p^R(i, j)$ has the class label c_3^R (that is, low intensity pixels) and the class label matrix element $C_2^T(i, j)$ is larger than a 50 percent of the total number of classification images as well, the fusion classification class label c_2^M is assigned to the final fusion classification label c_2^L .

(3) Transformation of FCCL C_3^M and creation of new class label C_4^L

If the initial classification class label $C_p^R(i, j)$ satisfies the condition $C_p^R(i, j) \neq c_3^R$, then the fusion classification class label is assigned to the final fusion classification label c_3^L . If the initial classification class label $C_p^R(i, j)$ has the class label c_3^R (that is, low intensity pixels) and the class label matrix element $C_2^T(i, j)$ is smaller than a 50 percent of the total number of classification images as well, a new class label is assigned to the final fusion classification label c_4^L .

(a)

(b)

Fig. 5. Test images (a) a part of TerraSAR-X satellite imagery taken on July 11, 2008 (Daejeon) (b) the corresponding Komsat-2 satellite imagery taken on September 13, 2008.

3. Experimental Results

The proposed algorithm was tested using co-registered TerraSAR-X satellite image taken on July 11, 2008 and Kompsat-2 satellite image taken on September 13, 2008 (Fig.5). The TerraSAR-X satellite image has Geocoded Ellipsoid Corrected

(GEC) product type. The image-to-image registration of two images was carried out using affine transformation model. The average registration errors for five control points were 1.76 pixel for row direction, 0.57 pixel for column direction, respectively.

Fig. 6 shows the fusion results of TerraSAR-X satellite image and Kompsat-2 satellite image

Fig. 6. The fusion results of TerraSAR-X satellite image and Kompsat-2 satellite image (a) $k_q = 0.1$ (b) $k_q = 0.2$ (c) $k_q = 0.3$ (d) $k_q = 0.4$ (e) $k_q = 0.5$ (f) $k_q = 0.6$ (g) $k_q = 0.7$ (h) $k_q = 0.8$ (i) $k_q = 0.9$.

Fig. 7. Partial enlargement of the fusion results of Fig. 5 (a) $k_q = 0.1$ (b) $k_q = 0.2$ (c) $k_q = 0.3$ (d) $k_q = 0.4$ (e) $k_q = 0.5$ (f) $k_q = 0.6$ (g) $k_q = 0.7$ (h) $k_q = 0.8$ (i) $k_q = 0.9$.

according to the fusion weight k_q , which varies from 0.1 to 0.9 with the interval 0.1. The amount of the pixels inserted from the Komsat-2 satellite imagery in the fused SAR/EO image increases as k_q increases. This is especially noticeable in the pixels in homogeneous intensity area of the Komsat-2

satellite image as shown in Fig. 7.

Fig. 8 shows the classification result of the fused images in Fig. 5 by MLC. The total number of the classes in the FCCL image is three, the same as the total number of the classes in the ICCL. While the high intensity pixels belonging to the strong

Fig. 8. Fusion Classification Class Label (FCCL) image. (a) $k_q = 0.1$ (b) $k_q = 0.2$ (c) $k_q = 0.3$ (d) $k_q = 0.4$ (e) $k_q = 0.5$ (f) $k_q = 0.6$ (g) $k_q = 0.7$ (h) $k_q = 0.8$ (i) $k_q = 0.9$.

backscattering in TerraSAR-X satellite image represents man-made objects, the high intensity pixels in Kompsat-2 satellite image are observed sometimes in the areas where man-made objects do not exist as shown in Fig. 9.

Table 4 shows the example of the transformation

Table 4. Transformation of the Fusion Classification Class Label (FCCL) c_2^M into the Final Fusion Classification Label (FFCL) c_2^L

FCCL	Condition	FFCL
c_1^M	$C_p^R(i, j) \neq c_3^R$	$c_1^M \rightarrow c_1^L$
	$C_p^R(i, j) = c_2^R$	$c_2^M \rightarrow c_2^L$
	$C_p^R(i, j) = c_3^R$	$c_3^M \rightarrow c_3^L$

Fig. 9. The change of the class labels in the fusion classification class label (FCCL) according to k_q .

Fig. 10. Example of the class label transformation (a) ICCL (b) FCCL (c) FFCL.

of the Fusion Classification Class Label (FCCL) c_2^M . Though the FCCL has high intensity pixels (c_1^M), the FCCL c_2^M is assigned to the Final Fusion Classification Label (FFCL) when the condition $C_p^R(i, j) = c_2^R$ is satisfied. This means the FFCL accept the initial

classification class label (medium intensity pixels) if the FFCL has high intensity pixels (c_1^M) and ICCL, however, has the medium intensity pixel. Fig. 10 shows one example of the class label transformation. Because the high intensity pixels along the vertical

Fig. 11. Comparison of the classification results (a) TerraSAR-X satellite image (b) Komsat-2 satellite image (c) ICCL image (d) FFCL image.

Table 5. Final Fusion Classification Label (FFCL) for the fused SAR/EO image

FFCL	Class Label Intensity	Land Property	Intensity Level
c_1^L	High intensity	Strong backscattering region	250
c_2^L	Medium intensity type 1	Homogeneous region	180
c_3^L	Medium intensity type 2	Non-homogmnrous region	90
c_4^L	Low intensity	Shadow, water	0

direction in the center of Fig. 10(b) have the class label c_1^M , while the initial classification class label $C_p^R(i, j)$ of those pixels has the class label c_1^R , the class label c_2^M is assigned to the FFCL of those pixels as shown in Fig. 10(c).

The type of the final fusion classification label (FFCL) due to the transformation process in Table 3 is listed in Table 5. The total number of the FFCL is four, while the total number of the initial classification class labels and the fusion classification

class labels is three. The pixels belonging to the class label c_2^R (medium intensity pixels) in the initial classification class label are classified into the two medium intensity types, the medium intensity type 1 (homogeneous region) and the medium intensity type 2 (non-homogeneous region). Fig. 11(c) and Fig. 11(d) show the ICCL image and the FFCL image for the fused TerraSAR-X/Komsat-2 image, respectively.

4. Conclusions

In this paper, we proposed the transformation rules combining the multiple classification results of the fused images into one classification result. The new definition of class label matrix element was proposed for the transformation of fusion classification class label (FCCL) to produce final fusion classification label (FFCL). Through the transformation of the FCCL into the FFCL, we created four final fusion classification labels for the fused SAR/EO image, which contained homogeneous intensity properties due to EO image. Future research concerning the combination of multiple classification will focus on fusing class labels concerning features of man-made objects in EO image with the final fusion classification label.

Acknowledgements

This study was supported by Korea Aerospace Research Institute through the program "Development Program of Korea Multi-Purpose SATellite-3 VII".

References

- Fatone, L., P. Maponi, and F. Zirilli, 2001. Fusion of SAR/optical images to detect urban areas, *Remote Sensing and Data Fusion over Urban Areas, IEEE/ISPRS Joint Workshop 2001*, 217-221.
- Garzelli, A., 2002. Wavelet-based fusion of optical and SAR image data over urban area, *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* 34(3): 59-62.
- Li, Z., Z. Jing, G. Liu, S. Sun, and H. Leung, 2003. A region-based image fusion algorithm using multiresolution segmentation, *IEEE Proceedings of 2003 Intelligent Transportation Systems*, 96-101.
- Long, Z. and W. Guangfang, 2007. Study on adaptation of SAR/CCD image fusion algorithm, *International Symposium on Photoelectronic Detection and Imaging 2007: Image Processing, Proceedings of SPIE*, 6623: 66230.
- Petrovic, V. and C. Xydeas, 2004. Gradient based multiresolution image fusion, *IEEE Transactions on Image Processing*, 4(2): 163-183.
- Piella, G., 2003. A general framework for multiresolution image fusion: from pixels to regions, *International Journal of Information Fusion*, 4: 258-280.
- Ye, C.S., 2009. Fusing optical and SAR images using wavelet transform and multiscale images, *Proceedings of International Symposium on Remote Sensing 2009*, Busan, Korea, Oct. 28-30, 520-523.
- Ye, C.S., 2010. Wavelet-based fusion of optical and radar image using gradient and variance, *Korean Journal of Remote Sensing*, 26(5): 581-591.