UNSUPERVISED CHANGE DETECTION METHOD FOR HYPERSPECTRAL IMAGE USING SPECTRAL SIMILARITY MEASUREMENT

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ABSTRACT

Hyperspectral data provides useful information for many imaging processes such as classification and target detection using hundreds of continuous and very narrow bands. In particular, change detection is one of the most important and challenging tasks in the field of hyperspectral imaging. A change detection method using hyperspectral data could provide more interpretable information on the nature of the change instead of identifying only the changed locations in a scene. In many cases, illumination change effects such as shadow effects have been considered one of the major problems for change detection. The illumination factors could be effectively mitigated by spectral similarity measures because the approach is relatively insensitive to shadow and albedo effects. In this study, the effectiveness of various spectral similarity measures, including original and hybrid measures, for charge detection was compared. Simulated data with changed areas and exaggerated noise were generated using CASI and Hyperion to test various similarity measures. The experimental results showed that hybrid measures such as SIDSCA could most efficiently discriminate the changed pixels. This is because SIDSCA combined the advantages of both SID and SCA. Hybrid measures could be used for various change detection applications. In the future, studies on real data and on determining threshold values to extract real changed pixels will be conducted.

INTRODUCTION

Hyperspectral images, which contain many spectral bands, show improved capability for many applications such as classification and target detection (Pu et al., 2014). Remote sensing data are key sources of change detection techniques, and many change detection methods have been developed thus far (Lu et al., 2004). Hyperspectral data could provide useful information for change detection through the use of spectral properties. However, environmental factors such as atmospheric conditions, illumination, viewing angle, and co-registration errors could still degrade the accuracy of change detection. One of the major problems is the illumination change effect caused by the difference in sun angle and atmospheric conditions. In particular, this factor is of significance in images with high spatial and spectral resolution.

The illumination change effect could be mitigated by using spectral similarity measures; however, this approach is relatively insensitive to shadow and albedo effects (Boltt et al., 2014). Therefore, it is important to find appropriate similarity measures that could mitigate the illumination effect for change detection. In this study, various spectral similarity measures were compared to find the most suitable unsupervised change detection method. Simulated images generated from the Compact Airborne Spectrographic Imager (CASI) and Hyperion were used for change detection, and the experimental results were analyzed using reference data.

METHODS

Many spectral similarity measures have been developed thus far. These are divided into deterministic and stochastic methods (Vishnu et al., 2013). Deterministic approaches such as Euclidean Distance (ED), Spectral Angle Distance (SAM), and Spectral Correlation Angle (SCA) consider the geometrical and physical aspects of signatures. ED is a computationally simple method in which the distance between two spectral signatures is calculated.

$$\mathrm{ED}(s_i, s_j) = \sqrt{\sum_{l=1}^{L}(s_{il} - s_{jl})^2} \qquad (1)$$

SAM and SCA are angle-based methods. SAM is a widely used method in which the angle between two signatures is measured. SCA uses the correlation between two spectral signatures in terms of angle.

$$\mathrm{SAM}(s_i, s_j) = \cos^{-1}\left(\frac{\sum_{l=1}^{L} s_{il}s_{jl}}{[\sum_{l=1}^{L} s_{il}^2]^{\frac{1}{2}}[\sum_{l=1}^{L} s_{jl}^2]^{\frac{1}{2}}}\right) \qquad (2)$$

$$\mathrm{SCA}(s_i, s_j) = \frac{\sum_{l=1}^{L}(s_{il}-\overline{s_{il}})(s_{jl}-\overline{s_{jl}})}{\sum_{l=1}^{N}(s_{il}-\overline{s_{il}})^2 \sum_{l=1}^{N}(s_{jl}-\overline{s_{jl}})^2} \qquad (3)$$

Stochastic measures including Spectral Information Divergence (SID) are based on the statistical aspects of spectral reflectance. SID is used to calculate the probability of spectral discrepancy.

$$\mathrm{SID}(s_i, s_j) = D(s_i||s_j) + D(s_j||s_i) \qquad (4)$$

$$D(s_i||s_j) = \sum_{l=1}^{L} p_l D_l(s_i, s_j) = \sum_{l=1}^{L} p_l \log\left(\frac{p_l}{q_l}\right) \qquad (5)$$

$$D(s_j||s_i) = \sum_{l=1}^{L} q_l D_l(s_j, s_i) = \sum_{l=1}^{L} q_l \log\left(\frac{q_l}{p_l}\right) \qquad (6)$$

$D(s_i||s_j)$ and $D(s_j||s_i)$ are derived from two probability vectors $p = (p_1, p_2, \cdots, p_l)^T$ and $q = (q_1, q_2, \cdots, q_l)^T$. p_k and q_k are defined as $p_k = s_{ik}/\sum_{l=1}^{L} s_{il}$ and $q_k = s_{jk}/\sum_{l=1}^{L} s_{jl}$, respectively.

Two or more measures could be combined to improve the limitations of the existing spectral similarity measures. Hybrid methods such as SIDSAM and SIDSCA show increased spectral matching accuracy (Vishnu et al., 2013). SIDSAM and SIDSCA are respectively defined as follows:

$$\mathrm{SIDSAM}(s_i, s_j) = \mathrm{SID}(s_i, s_j) \times \tan(\mathrm{SAM}(s_i, s_j)) \qquad (7)$$

$$\mathrm{SIDSCA}(s_i, s_j) = \mathrm{SID}(s_i, s_j) \times \tan(\mathrm{SCA}(s_i, s_j)) \qquad (8)$$

Although both tangent and sine trigonometric functions could be applicable, the former were used because they usually have a higher similarity value than the latter (Naresh et al., 2011).

RESULTS

1) Simulated data set 1

Simulated data sets were used to compare the change detection capabilities. Simulated data set 1 was generated from CASI; it consists of 100×100×48 pixels. The spatial resolution of CASI is 1 m, and its spectral range is 0.37–1.05 nm. Additive Gaussian white noise (30 dB) was randomly added to the simulated images to create an environment similar to real situations (defined noise type 2).

However, SCA does not consider the offset factor (Carvalho et al., 2011). Simply added noise could not affect the SCA similarity measures. Therefore, Gaussian noise was multiplied with the original images to produce exaggerated noise and change the spectral signatures (defined noise type 2). Figure. 1 shows the simulated data set 1.

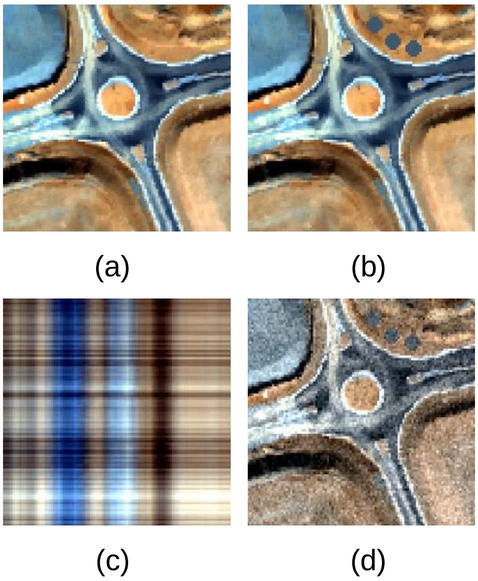


Figure 1. RGB images for simulated data set 1: (a) original, (b) simulated, (c) added noise type 1 to original image, and (d) added noise type 2 to simulated image.

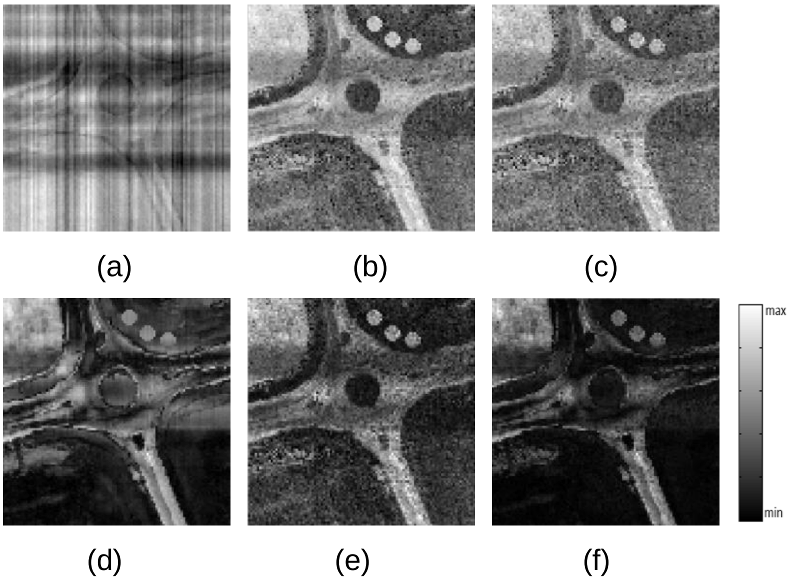


Figure 2. Similarity maps between original and simulated images by using (a) ED, (b) SAM, (c) SID, (d), SCA, (e) SIDSAM, and (f) SIDSCA.

Figure 2 shows the similarity values between original image with noise type 1 and simulated image with added noise type 2. ED was significantly affected by the noise (Figure 2(a)) because it is sensitive to the differences in the reflectance value. Other measures showed distinct values in changed areas. The performance of the hybrid measures was better than that of the original measures. In particular, SIDSCA could efficiently discriminate the changed area from the other pixels

(Figure 2(f)). This is because SCA is insensitive to the gain and offset factors, and SID tends to make two dissimilar signatures more distinct.

The ROC curve illustrates the performance of binary classification as its discrimination threshold is varied. The accuracy is measured by the shape of the curve and the area under the ROC curve (AUC). An area of 1 represents a perfect test. Figure 3 and Table 1 show the ROC curve and AUC of six measures in simulated data set 1. Among the original methods, SAM and SCA efficiently discriminate changed areas. SIDSCA had the highest AUC value, indicating that it could efficiently discriminate the changed areas.

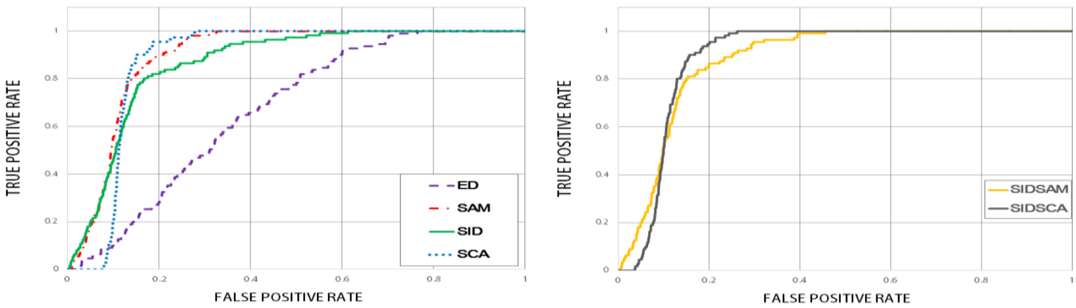


Figure 3. ROC curves for simulated data set 1

Table 1. AUC values of spectral similarity measures in simulated data set 1

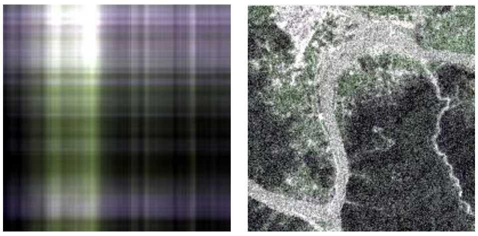
	ED	SAM	SID	SCA	SIDSAM	SIDSCA
AUC	0.6734	0.8916	0.8645	0.8792	0.8804	0.8928

2) Simulated data set 2

The simulated data set 2 was generated using Hyperion. Hyperion provides 220 spectral bands (from 0.36–2.58 nm) with 30-m spatial resolution. Simulated data set 2 contained randomly added Gaussian white noise (SNR: 25 dB); red areas represented the changed pixels.

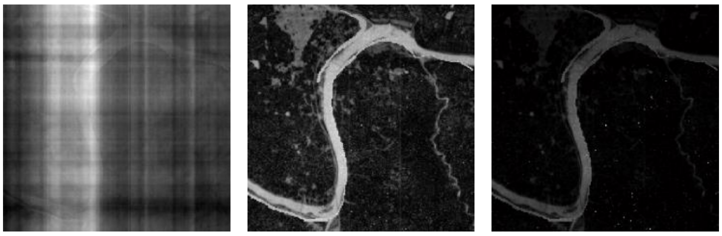
Figure 5 showed the similarity maps from various spectral similarity measures. ED was also significantly affected by the noise, and it could not discriminate the changed pixels. In particular, the river areas showed more dissimilar values. This is because they are relatively higher values than background pixels. According to the ROC curve and AUC, five measures except ED could discriminate the changed area. SCA was the most efficient method among the original methods, and SIDSCA had the highest AUC value.

(a) (b)

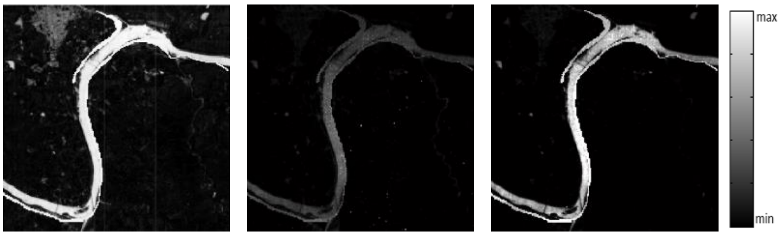


(c) (d)

Figure 4. RGB images for simulated data set 2: (a) original, (b) simulated, (c) added noise type 1 to original image, and (d) added noise type 2 to simulated images.



(a) (b) (c)



(d) (e) (f)

Figure 5. Similarity maps between original and simulated images using (a) ED, (b) SAM, (c) SID, (d), SCA, (e) SIDSAM, and (f) SIDSCA.

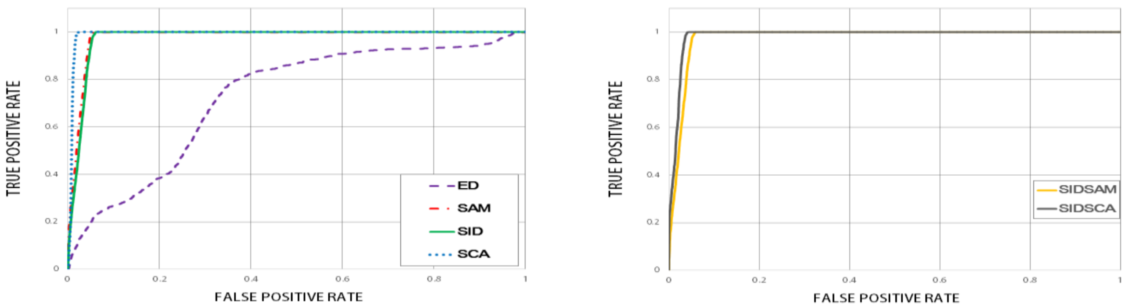


Figure 6. ROC curves for simulated data set 2.

Table 2. AUC values of spectral similarity measures in simulated data set 2

	ED	SAM	SID	SCA	SIDSAM	SIDSCA
AUC	0.7239	0.9792	0.9756	0.9921	0.9770	0.9853

The AUC value of SIDSAM was lower than that of SAM. The combination of SAM and SID showed worse performance. Unlike SIDSAM, SIDSCA showed better performance than SAM and SCA. The combination of SID and SCA was efficient for change detection.

CONCLUSIONS

Spectral similarity measures could be used for change detection without illumination effects. To find appropriate measures for change detection, original and hybrid spectral similarity measures were used.

The experimental results showed that hybrid measures such as SIDSCA were more efficient for change detection than SID and SAM alone. This is because the hybrid measures combined the advantages of both original measures. SIDSCA could discriminate changed pixels efficiently because SID tends to make dissimilar signatures more distinct and SCA is insensitive to gain and offset errors. SIDSCA could be used for many change detection applications. Studies on determining threshold values will be conducted as future work.

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REFERENCES

Pu, H., C. Zhao, B. Wang, and G.M. Jiang, 2014, A Novel Spatial-Spectral Similarity Measure for Dimensionality Reduction and Classification of Hyperspectral Imagery, IEEE Transaction on Geoscience and Remote Sensing, 52(11), pp.7008-7022.

Lu, D., P. Mausel, E. Brondízio, and E. Moran, 2004, Change Detection Techniques, International Journal of Remote Sensing, 20(12), pp.2365-2407.

Boltt, M., C. Ndegwa, and P. Pellikka, 2014, Using Hyperspectral Data to Identify Crops in a Cultivated Agricultural Landscape: A Case Study of Taita hills, Kenya, Earth Science and Climatic Change, 5(9), pp. 232-236.

Vishnu, s., R.R Nidamanuri, and R, Bremannanth, 2013, Spectral Material Mapping Using Hyperspectral Imagery: A Review of Spectral Matching and Library Search Methods, Geocarto International, 28(2), pp.171-190.

Naresh Kumar, M., V.R. Seshasai, K.S. Varsa Prasad, V. Kamala, K.V. Ramana, R.S. Dwivedi, and P.S. Roy, 2011, A New Hybrid Spectral Similarity Measure for Discrimination among Vigna Species, International Journal of Remote Sensing, 32(14), pp.4041-4053.

Carvalho, J.O.A., R.F. Guimarães, A.R. Gillespie, N.C. Silva, and R.A.T. Gomes, A New Approach to Change Vector Analysis using Distance and Similarity Measures, Remote Sensing, 3(11), pp.2473-2493.