Automatic Spectral Signature Extraction for Hyperspectral Target Detection

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***Abstract*—There are two main approaches to hyperspectral target detection: anomaly detection techniques, which detect outliers substantially different from the background, and spectral signature techniques, which require as an input a user-defined target signature. Oftentimes, however, the target signature may not be known, or there may be unexpected targets in the image, which are unknown but still of interest. As a result, algorithms that can automatically extract potential target signatures without any *a priori* knowledge are of great interest. In this work, a fusion-based algorithm is developed that takes advantage of both spatial and spectral information to automatically extract the spectral signatures of potential targets of interest. The performance of several target detection algorithms is compared for both the proposed spatially-spectrally estimated (SSE) target signature and the initial target signature used by the Automatic Target Detection and Classification Algorithm (ATDCA). It is shown that the SSE signature leads to improved automatic spectral target recognition (ATSR) performance than the ATDCA algorithm for the test conducted on the AVIRIS Indian Pines dataset.**

Keywords—hyperspectral target detection, anomaly detection, spectral target recognition

I. Introduction

Automatic target detection in hyperspectral imagery is an important and challenging problem. Depending on the resolution of the hyperspectral image relative to the size of the target, the target footprint may either be sub-pixel or span several pixels. Anomaly detection techniques detect outliers whose spectral signature is substantially different from that of neighboring background pixels. Spectral-signature based techniques, however, required as input a user-defined target signature. In the case of an unknown target residing in an unknown image background, however, neither the spatial (multi-pixel versus sub-pixel) nor the spectral properties (i.e. target signature) are known *a priori*.

In 2003, Ren et. al. [1] proposed an Automatic Target Detection and Classification Algorithm (ATDCA) for automatic spectral target detection (ASTD), which used an automatic target generation process (ATGP) to compute the endemember subspace. Orthogonal Subspace Projection (OSP) is then applied to suppress the background subspace and a matched filter is used to generate detection results. However, ATGP requires the provision of an initial target signature to begin the endmember generation process. In ATDCA, the initial target signature $\boldsymbol{t_0}$ is set as the spectral signature of maximum length: $\mathbf{t_0} = \arg\left\{\max_{\mathbf{r}}\left(\mathbf{r}^T\mathbf{r}\right)\right\}$, where $\boldsymbol{r}$ is the matrix of spectral signatures of the pixels in the image. Thus, the initial signature provided to the algorithm in fact may not necessarily correspond to a true target signature.

In this work, a fusion-based algorithm for estimating potential target signatures is proposed. More specifically, spatial and spectral indicators are first fused to eliminate background regions of the image which are seen to have a very low probability of containing any targets. The remaining regions, defined as "probable target" regions are then searched for potential targets using two alternative methods: anomaly detection and image processing of spatial abundance variations to extract pixels likely to contain targets. The spectral signatures of these pixels are then declared as initial target spectra and supplied to target detection algorithms.

Furthermore, performance gains acheived by using the Optical Real-Time Adaptive Spectral Imaging System (ORASIS) developed by the U.S. Naval Research Laboratory are analyzed in comparison to the ATGP algorithm used by ATDCA. A variety of target detectors are also compared, including an automatic target recognition (ATR) extention [2] of ORASIS, OSP, and matched filter (MF). Results show that superior ASTR performance can be achieved when the proposed spatial-spectral estimation (SSE) algorithm is used to extract target signatures.

II. Automatic Signature Extraction

A. Background Elimination

The first step in the proposed method involves applying spatial analysis to discard regions of the image that are unlikely to contain any targets of interest. Two algorithms are implemented to independently identify and eliminate background pixels: 1) k-means clustering; and 2) global normalized RX anomaly detection. Spectrally homogeneous areas that are found to not contain any targets are thus eliminated from subsequent stages of target searching.

K-means clustering is utilized to spatially group spectrally similar pixels. Pixels forming closed clusters are marked as regions in which potential targets may be present, which the remaining are discarded as background. The Global Normalized RX (NRX) algorithm is utilized to detect anomalies because according to a comparative study by

Soofbaf, et.al. [3], the global RX yielded the highest false alarm rate among all anomaly detection algorithms. A NAND fusion rule is applied on the results from these algorithms to define an initial background mask that will be discarded from further target searches.

B. Probable Target Pixel Detection

The second step in the proposed algorithm is determine probably target pixel locations using two methods: 1) nested spatial window-base target detection (NSWTD) [4], shown to give the highest number of correct detections, and 2) image processing of endmember abundance maps. Abundance maps of endmembers can be generated using any of several possible endmember extraction algorithms, afterwhich texture and clustering analysis is employed to find the endmember most likely to correspond to a target signature. Centroids of contiguous regions are selected as potential target locations. Endmember spectra of these selected pixels are then compared in terms of spectral angle to the signatures of anomalies detected by NSWTD. Signatures shown to be sufficiently spectrally distinct are then saved as potential target signatures.

Note that with this method it is possible for multiple spectral signatures to be designated as potential target signatures. Each signature is independently used in the target detection stage. Afterwards, detection results are fused with an OR operation to give the total target detection results.

A flow chart summarizing the proposed SSE algorithm for target signature extraction is shown in Figure 1 below.

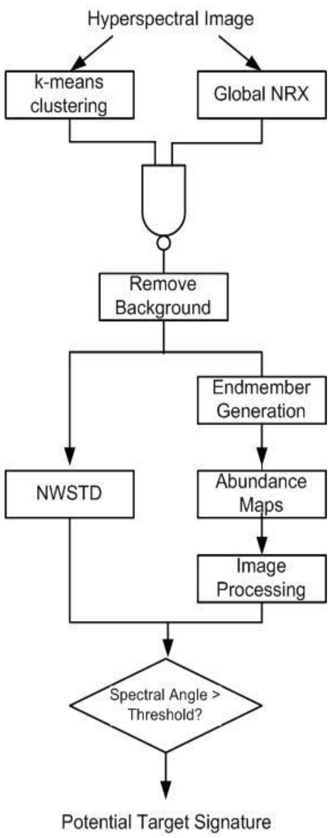

Figure 1. Flow chart for SSE signature extraction algorithm.

III. TARGET DETECTION

In the ATDCA algorithm, following the computation of an initial target signature, ATGP is used to compute the endmember subspace, followed by OSP to suppress the background subspace and MF to yield detection results. In this work, several different combinations of endmember generation and detection algorithms are compared in terms of performance, namely ATGP versus ORASIS for spectral unmixing, as well as ATR, OSP, and MF for target detection. Each of these algorithms are briefly summarized in turn.

A. ATGP

The ATGP algorithm requires as input an initial target signature, t_0. The orthogonal subspace to this target signature is defined as $P_{t_0}^{\perp}$, which is applied to all image pixels. The pixel signature with the maximum orthogonal projection in the complementary orthogonal space is defined as the next target signature, t_1. The next signature is then found by applying the orthogonal subspace projector $P_{[t_0 \backslash t_1]}^{\perp}$ and selecting the maximum orthogonal projection as t_2. The process continues until a stopping criterion is met: the orthogonal projection correlation index (OPCI) is defined as $\eta_i = t_0^T P_{t_0}^{\perp} t_0$ and is used to measure the similarity between two consecutive target signatures. When the OPCI exceeds a predefined threshold, the ATGP process stops.

B. ORASIS

The ORASIS algorithm was developed to spectrally unmix hyperspectral pixels according to a linear mixing model. Several versions have evolved over the years since its initial publication in 1999 [5] and subsequent improvements [6] were developed. The ORASIS algorithm may be decomposed into several steps: 1) noise reduction, 2) exemplar extraction, and 3) endmember generation. Noise reduction may be accomplished using any of a number algorithms. In this work, a multiple regression theory-based approach [7] that has been reported to perform well in practice was utilized.

Next, a smaller subset of spectra (called exemplars), which are representative of the entire image are computed by only storing those spectra that are deemed to be sufficiently different in spectral angle. These exemplars are then used as inputs to a simplex optimization process in which an initial basis is defined by orthogonalization of the two exemplar signatures with the greatest difference in spectral angle, known as salients. Vertex Component Analysis (VCA) is then used to compute the remaining endmembers, which are employed to initialize the application of Minimum Volume Simplex Analysis (MVSA) [8].

In this way, the ORASIS algorithm attempts to find the minimal number of endmembers that span all exemplar spectra. Ideally, it is aimed for a vertex of the endmember simplex to correspond to the spectral signature of the target desired. The greater the difference between the target signature and remaining background endmembers, the more likely it is for the target detection algorithms to successfully detect the presence of a target.

Indeed, ORASIS can also be used to form more accurate abundance maps using the following relation:

$$\alpha = PE, \quad (1)$$

where P is the Moore-Penrose pseudoinverse [9] of the exemplar matrix S:

$$P = \left(S^T S\right)^{-1} S^T. \quad (2)$$

C. ATR

The Automatic Target Recognition (ATR) algorithm [6] was originally proposed as an extention for target detection using the ORASIS algorithm; however, it may be applied using the endmembers of any spectral unmixing algorithm. Target identification is accomplished by projecting the scene spectra and the target spectrum into the subspace which is spanned by the extracted endmembers. Subsequently, the target spectrum and the scene spectra are compared in terms of spectral diversity by calculating the spectral angle between them. If the angle is less than an automatically calculated threshold then the pixel is classified as a target.

The threshold value can be automatically calculated with following steps: as the output of the ORASIS algorithm is utilized, it is assumed that the rejection statistics $r_1, \dots, r_m$, endmembers $E_1, \dots, E_n$ and exemplars $X_1, \dots, X_m$ have all been found. Next, let X_i^p be the projection of i-th exemplar into the endmember subspace. Assuming a linear mixing model, the X_i^p can be written as

$$X_i^p = \sum_{j=1}^{n} \sigma_{ij} E_j \quad (3)$$

where E_j are endmembers and σ_{ij} are abundance fractions. The projected target spectrum T^p can be written as

$$T^p = (\beta_1, \beta_2, \dots, \beta_n) \quad (4)$$

For each exemplar X_i, the θ_i namely the cosine of the angle between the projected exemplar X_i^p and the projected target spectrum T^p is defined by

$$\theta_i = \frac{\sum_{j=1}^{n} \sigma_{ij} \beta_j}{\sum_{j=1}^{n} \sigma_{ij}^2 \sum_{j=1}^{n} \beta_j^2} \quad (5)$$

Eventually, the threshold θ_t can be calculated by using the θ_i's calculated from (5):

$$\theta_t = \langle \theta_i \rangle + 3\sigma(\theta_i) \quad (6)$$

Here $\langle \theta_i \rangle$ denotes the mean of θ_i's weighted by the rejection statistics; r_i and $\sigma(\theta_i)$ denotes the standard deviation of the θ_i's.

IV. Results

The RGB bands of the AVIRIS Indian Pines dataset [10] is shown in Figure 2. Black points within the red rectangles indicate target locations, whose spectra are generated from a mixture of randomly selected pixel spectra.

Figure 2. RGB image of AVIRIS Indian Pines dataset

Figure 3 shows the target detection results obtained with the ATDCA method. Note that there are some false alarms as well as target leakage.

Figure 3. Result of ATDCA method

Figure 4 shows the result produced with the proposed method, which shows an improvement in results as compared to ATDCA.

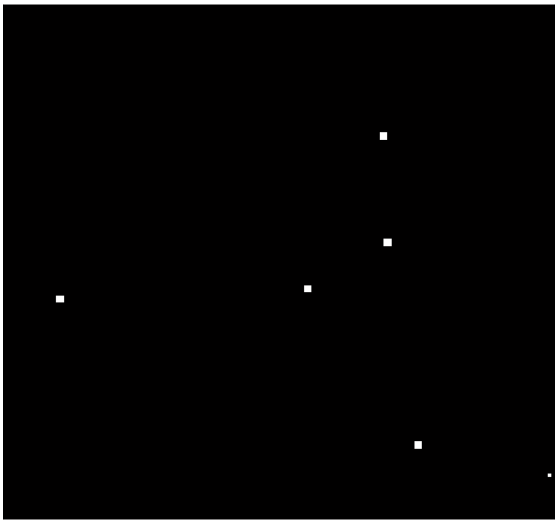

Figure 4. Result of SSE method

In order to make further comparison of both methods, receiver operating characteristics (ROC) analysis was employed. Figure 5 and 6 shows ROC curves for SSE and ATDCA methods respectively. SSE method finds nearly all targets with a lower false alarm rate, thereby rendering improved performance over ATDCA.

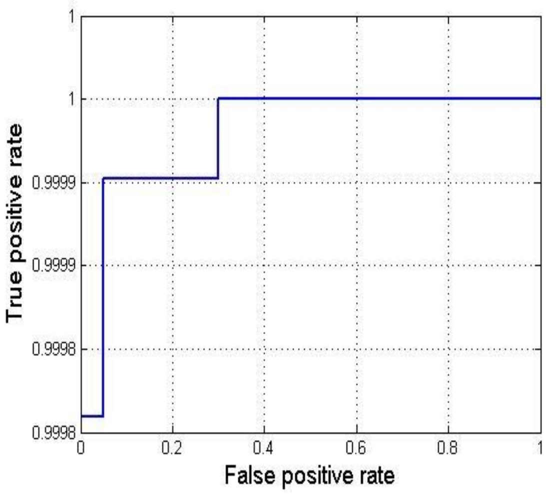

Figure 5. ROC curve obtained from the result of SSE

I. CONCLUSION

In this work, a fusion-based algorithm is developed that takes advantage of both spatial and spectral information to automatically extract the spectral signatures of potential targets of interest. The target signature is not assumed to be known a priori. Instead, the reference target signature is extracted from the image using a fusion of spatial and spectral analysis. The performance obtained using the Spatial-Spectral Estimate (SSE) target signature and the initial target signature used by the Automatic Target Detection and Classification

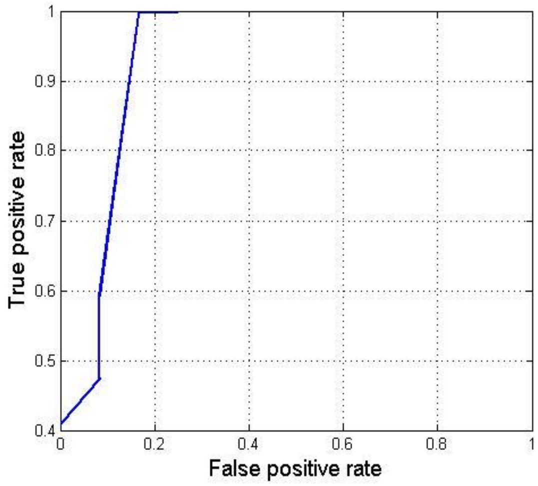

Figure 6. Roc curve obtained from the result of ATDCA

Algorithm (ATDCA) are compared. It is shown that the SSE signature leads to improved automatic spectral target recognition (ATSR) performance than the ATDCA algorithm for the test conducted on the AVIRIS Indian Pines dataset.

REFERENCES

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REFERENCES

[1] Ren, H. and Chang, C.-I, “Automatic spectral target recognition in hyperspectral imagery,” IEEE Trans. Aerospace and Electronic Systems, Vol. 39, No. 4, October 2003.

[2] Gillis, D., Palmadesso, P.J., Bowles, J.H., “Automatic target recognition system for hyperspectral imagery using ORASIS,” in Proc. SPIE 4381, August 20, 2001.

[3] Soofbaf, S.R., ValadanZoej, M.J., Fahimnejad, H., and Ashoori, H., “Efficient detection of anomalies in hyperspectral images,” in Proc. ISPRS Congress XXXVII, Beijing, 2008.

[4] Liu, W., “A nested spatial window-based approach to target detection for hyperspectral imagery,” IEEE 1(20), pp. 264-268, 2004.

[5] Bowles, J., Chen, W., and Gillis, D., "ORASIS framework-benefits to working within the linear mixing model." IEEE Geoscience and Remote Sensing Symposium, 2003.

[6] Bowles, J., Gillis, D. and Palmadesso, P., "New improvements in the ORASIS algorithm." IEEE Aerospace Conf. Proceedings, Vol. 3., 2000.

[7] Bioucas-Dias, J.M., and Nascimento, J.M.P., "Hyperspectral subspace identification." IEEE Trans. On Geoscience and Remote Sensing, Vol. 46, No. 8, pp. 2435-2445, 2008.

[8] Li, J., and Bioucas-Dias, J.M., "Minimum volume simplex analysis: A fast algorithm to unmix hyperspectral data." IEEE Geoscience and Remote Sensing Symposium, 2008.

[9] Grossmann, J.M., Bowles, J.H., Haas, D., Antoniades, J.A., Grunes, M.R., Palmadesso, P.J., Gillis, D., Tsang, K.Y., Baumback, M.M., Daniel, M., Fisher, J., and Triandaf, I.A., “Hyperspectral analysis and target detection system for the Adaptive Spectral Reconnaissance Program (ASRP),” in Proc. SPIE, Vol. 3372, pp. 2, 1998

[10] [Online]. Available: http://cobweb.ecn.purdue.edu/~biehl/MultiSpec/documentation.html