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A Modified Multiple Properties Constrained Target Detection Algorithm Based on Extended Morphology for Hyperspectral Imagery

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Abstract. We proposed an improved target detection algorithm for Hyperspectral Imagery, referred as EXmorMPCTD (extended morphology based Multiple Properties Constrained Target Detection). By comparing the spectral difference between targets and sample pixels of hyperspectral image and selecting the pixels with conspicuously different spectral characteristic with targets to construct the background characteristic matrix, efficiently reduces the interference information and improves the accuracy of background characteristic matrix extremely. We carried out the validation test of the proposed algorithm. The results show that the detection accuracy of the traditional algorithms MCEM, ACE, OSP and TCIMF is 0.9264, 0.9057, 0.8843 and 0.8581, while the detection accuracy of the proposed algorithm in this paper reaches 0.9922. The DI（Detection Index） is also increased from 0.611,0.608,0.601 and 0.5940 of the traditional algorithms MCEM, ACE, OSP and TCIMF to 0.669 of the proposed algorithm in this paper.

Keywords. Hyperspectral target detection, extended Morphology, DI.

1. Introduction

Hyperspectral target detection makes full use of continuous and abundant reflectance spectrum, which can represent the diagnostic feature of substance[1-3] of hyperspectral image to differentiate targets and background. There are various algorithms developed in recent 20 years in this field, these algorithms can be classified into three classes according to how well we mastered the priori intelligence, that is, unknown target and background algorithm, unknown background but known target algorithm, known target and background algorithm. Some of those algorithms are so practical that many improved approaches were developed according to their principle. Those practical and typical algorithms include signal theory based Constrained Energy Minimization (CEM) algorithm[4], probability statistics model based Adaptive Coherence/Cosine estimator (ACE) algorithm[5]and Adaptive Matched Filter(AMF)algorithm[6], linear mixture model and subspace model based Orthogonal Subspace Projection (OSP) algorithm[7]

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and anomaly detection algorithms, RXD(Reed and Yu Detector)[8-10] UTD(Uniformed Target Detector)and LPTD(Low Probability Target Detector)[11].

We need both targets and background information, which usually cannot be acquired completely, when we conduct OSP algorithm. What's more, the performance of suppressing noise and eliminating unknown signal of OSP algorithm is poor[12]; Anomaly detection algorithm does not require a priori information of the target or background spectrum, only regarding the pixels whose spectral characteristics do not meet the global or local background spectrum signal model as targets, but these abnormalities are not necessarily the target of interest[13-14].in addition, these abnormalities include some interference information at a very definite possibility[15-16]such as noise and non-targets with low energy or little abundance.

Harsanyi proposed CEM algorithm, Kraut and Scharf proposed ACE algorithm, Fuhrmann proposed AMF algorithm which all only need the spectrum of targets to solve the problems above. Those algorithms are more target oriented compared to anomaly detection algorithms and more competent than OSP algorithm to suppress noise and eliminate unknown signal. But both ACE and AMF are only suit for the normal distributed hyperspectral data while hyperspectral data usually meets manifold distribution model[17]. The performance of CEM algorithm is irrelevant with the distribution of hyperspectral data. So in many case, CEM algorithm is more practical. But it has evidenced that CEM cannot classify the same type of targets with similar signatures and it's sensitivity to noise do not improved substantially than OSP algorithm. In order to solve this problem, Chein-I Chang and Du Q et al considered general approaches, Multiple-Target CEM (MCEM), Sum CEM(SCEM) and Winner-Take-All CEM (WTACEM)[18].Those general approaches can not only solve CEM's sensitivity to target spectrum and lack of noise discrimination, but also break through the limitation of single target detection. We usually detect the targets one by one or one signature by one signature when we need to detect more than one targets or target with more than one spectral feature. But in this way, on one hand, the efficiency of detection must decrease sharply, especially in the case of real time detection. On the other hand, we cannot weed out the false alarm by the figure of detection result. So those improved algorithms integrate the advantages of multiple properties target detection, noise suppressing and insensitivity to spectrum.

But, similar with CEM, those approaches also ignore the impact of target on the background statistics. Considering the same mathematic principle and similar formula form between CEM and MCEM, this paper proposed an improved algorithm using extended morphology method to address this problem of MCEM. Taking the weak ability of traditional 2D ROC to identify subtle difference between two detectors into consideration, this paper employs DI (Detection Index) which generated by 3D ROC[19-20](three dimensional receiver operational characteristics) to access the detection precision completely..

2. Proposed Algorithm

As is known , in case of no information of background, the classical hyperspectral target detection algorithms evaluate the approximate background information by information of whole image. That is, background characteristic matrix R includes the information of targets. In order to eliminate the auto correction matrix of targets in R, this paper uses orthogonal projection divergence based extended morphological erode operator, which removes the targets first, to extract the information of background.

Firstly, based on spatial resolution of hyperspectral images and information of target size, a mobile operation window, which is larger than the size of target, is designed. In the window, The accumulated distance between the pixel (x, y) and other pixels is as follows.

$$D[f(x,y), w(\hat{x},\hat{y})] = \{\sum_{i=1}^{\hat{x}} \sum_{i=1}^{\hat{y}} \mathrm{distance}[f(xi,yi), w(\hat{x},\hat{y})] \mid (xi,yi) \in D_f, (\hat{x},\hat{y}) \in D_w\} \quad (1)$$

Where: Df and Dw represents the definition domain of the hyperspectral image and the extended morphological window, distance represents the linear distance between two n-dimensional vectors, and the distance is calculated using the orthogonal projection divergence derived from the orthogonal subspace projection principle,OPD distance calculation method seen in literature[21].

Secondly, after calculating the accumulated distance between each pixel in the structural element and other pixels, the pixel with the smallest accumulated distance can be found, and the corrosion calculation of formula (2) can be obtained.

$$Erode(x,y) = (f \ominus w)(x,y) = Min(\sum_{i=1}^{\hat{x}*\widehat{y-1}} OPD[f(xi,yi), w(\hat{x}i,\hat{y}i)]) \quad (2)$$

Eventually,After the pixel with the smallest difference from the background in the structural element is obtained, all the pixels in the structural element are replaced by the pixel, and then the position of the extended morphological window moves by pixel and repeats the calculation process until the entire image is calculated. All target information is completely filtered out.

This paper extracts background information of hyperspectral image by this method. The process of target detection can be divided into the following steps.

(a) Reading the data of hyperspectral imagery.

(b) According to the target size and image resolution size, the size of the mobile calculation window is determined.

(c) From the original pixel of the image (default left upper corner), the erosion operation based on expanded morphology is used to obtain the pixel in structural element, which is most largely similar to the background's. Then this pixel replaces all pixels in structural element.

(d) Image-by-pixel mobile operation window means that the pixels with the largest similarity of background is successively obtained until all pixels are traversed. At this time, background information is obtained.

(e) Using the background characteristic matrix acquired by the above steps replaces R in the original classical algorithm model.

(f) The improved algorithm——EXmorMPCTD（extended morphology based Multiple Properties Constrained Target Detection）is used to detect target.

(g) Algorithm execution completed.

In order to better evaluate the advantages of the algorithm proposed by this paper,we construct detection index(DI) model according to 3DROC proposed in literature 19.

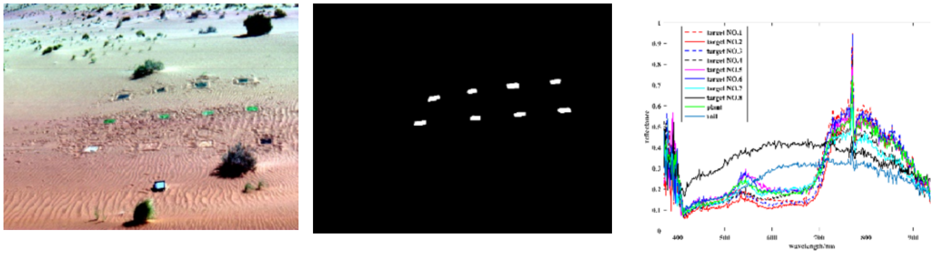
$$DI = \frac{area(T,pd)*area(pf,pd)-area(T,pf)}{area(T,pd)*area(pf,pd)} \quad (3)$$

Where: area(pf, pd) represents the area of 2DROC in 3DROC model, T is the threshold vecter, pf is false alarm vecter, pd is the detection vecter.

3. Experiments and Results

3.1. Experimental Data

We used the hyperspectral image acquired by the spectrometer as true experimental data. This data has 221 valid bands in range of visible and near infrared when eliminated the bands with low SNR (Signal Noise Ratio).We used eight fabrics with color of light green, medium green, dark green as multiple spectral properties targets, as shown in figure1(a). The background is composed of pants, soil and some stones. this data consists of 300×400 pixels while targets contain 50 pixels, the distribution of targets is displayed in figure1(b), We designed this data by considering the spectrum of pants and targets were similar as shown in figure 1(c).

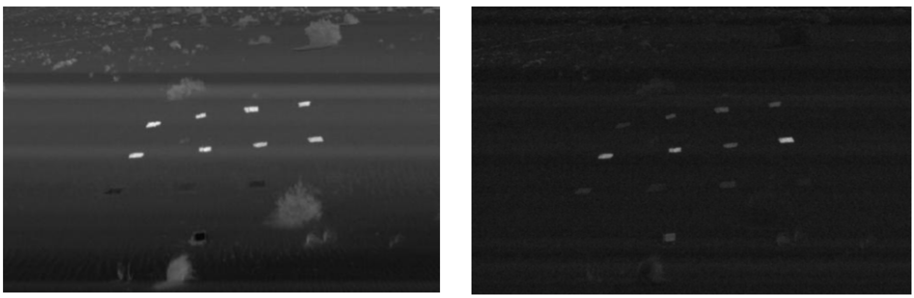


(a) True hyperspectral image (b) distribution of targets (c)Spectrum of true data

Figure 1. Experimental data

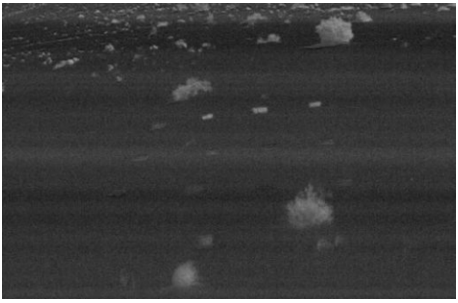
3.2. Detection Results of True Data

EXmorMPCTD algorithm proposed by this paper and other classical hyperspectral target detection algorithms, such as MCEM, ACE, OSP, TCIMF, were conducted respectively to detect the targets in experimental image data.the detection results are listed in figure 2. According to the distribution of targets shown in figure 1, the detection result of EXmorMPCTD is the best from the perspective of visual effect.

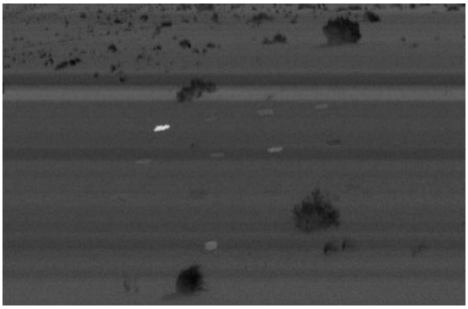


(a)detection result of EXmorMPCTD (b)detection result of MCEM

(c)detection result of ACE



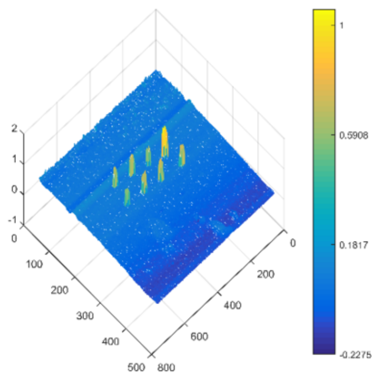
(d)detection result of OSP



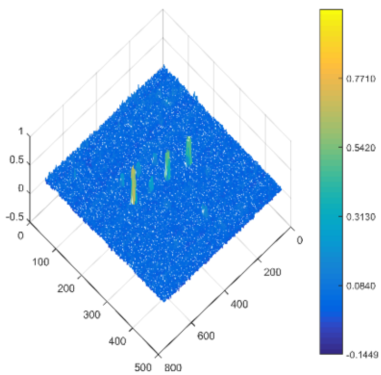
(e)detection result of TCIMF

Figure 2. Detection results of true data

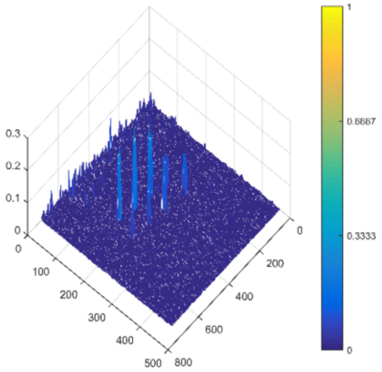
Own to the spectral similarity between targets and principal component of background, there are some false alarms around targets in the detection result of MCEM, ACE, OSP and TCIMF, as shown in figure 3(b)-(e), We can get the information that some background detection value even larger than targets detection value.In contrast, the EXmorMPCTD algorithm proposed by this paper suppresses the background and highlights the targets effectively seen in figure 2(a) and figure 3(a), which describe the superiority of EXmorMPCTD algorithm graphically.



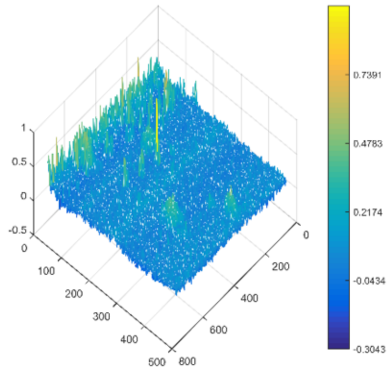
(a)detection statistics of EXmorMPCTD



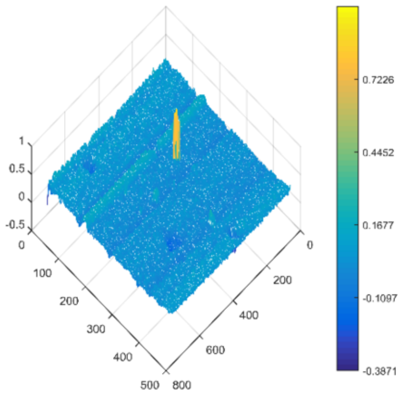
(b)detection statistics of MCEM



(c) detection statistics of ACE



(d) detection statistics of OSP



(e)detection statistics of TCIMF

Figure 3. 3D detection statistics for true data detection result

The result of detection accuracy evaluation were displayed in figure 4 and table 1. Figure 4 shows the 3D ROC of detection results, table1 shows the 2D AUC, AI value of five detectors. we can already estimate the performance of EXmorMPCTD algorithm and other five classical algorithms by traditional 2D AUC (0.9922 vs 0.9264,0.9057,0.8843,0.8581). Even though the background detection value of MCEM is a little smaller than EXmorMPCTD, the targets detection value is far smaller than the counterpart of EXmorMPCTD.So,as seen in table 1, EXmorMPCTD acquires the AI with larger value. What is more, EXmorMPCTD assures all the targets detection value larger than background detection value, which is the key to improve the detection accuracy.

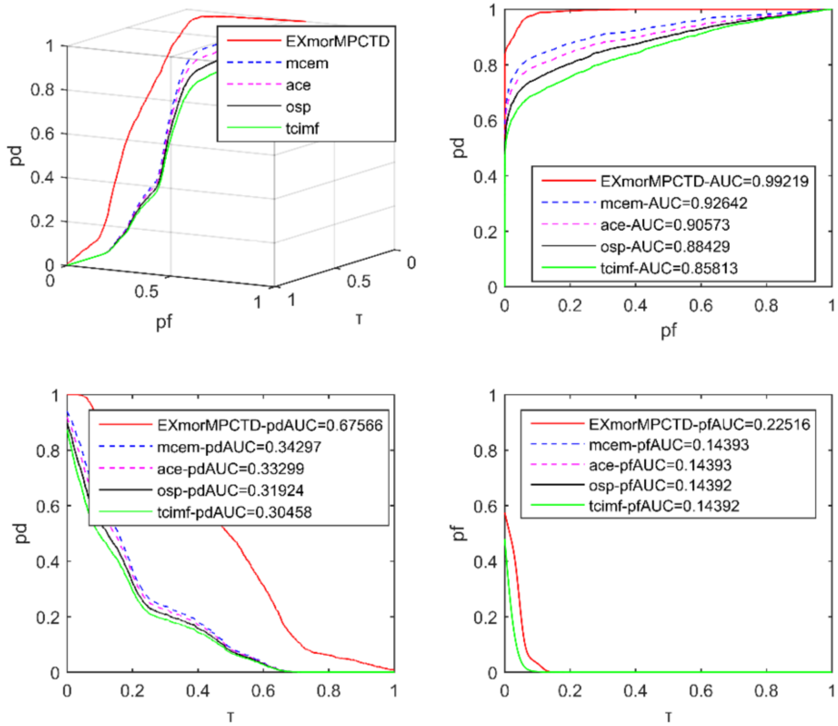


Figure 4. 3D ROC of detection result for true data

Table 1. Accuracy of detection results for true data

Method	$AUC_{(pf,pd)}$	$AUC_{(T,pd)}$	$AUC_{(T,pf)}$	DI
EXmorMPCTD	0.9922	0.6757	0.2252	0.669
MCEM	0.9264	0.3430	0.1439	0.611
ACE	0.9057	0.3330	0.1439	0.608
OSP	0.8843	0.3192	0.1439	0.601
TCIMF	0.8581	0.3046	0.1439	0.594

4. Conclusion

In this paper, we proposed a modified algorithm called EXmorMPCTD for hyperspectral multiple targets detection. Different from the classical algorithms such as MCEM, ACE,OSP and TCIMF, EXmorMPCTD construct a more precise background characterictics matrix by eliminating the pixels with targets spectral properties first. As a result, impact of targets on background statistics is lessened substantially. Additionally, this paper also proposed DI (Detection index) which can be calculated from 3D ROC to overcome the shortcoming of traditional 2D ROC accuracy evaluation method. We used true data to verify this modified algorithm and the experimental results estimated by this proposed accuracy assessment method, demonstrated that EXmorMPCTD owns superior performance than the classical algorithms.

References

[1] ZHAO Y S, et al.The Principles and Methods for Analysis and Appli cation of Remote Sensing. Beijing: Science Press, 2003.

[2] Zhang L P . Advance and Future Challenges in Hyperspectral Target Detection[J]. Wuhan Daxue Xuebao (Xinxi Kexue Ban)/Geomatics and Information Science of Wuhan University, 2014, 39(12):1387-1394 and 1400.

[3] Qing X T , Bing Z , Li F Z . Current progress of hyperspectral remote sensing in China[J]. Journal of Remote Sensing, 2016, 20(5): 689–707.

[4] Harsanyi, Joseph C . Detection and classification of subpixel spectral signatures in hyperspectral image sequences [D].Baltimore: Department of Electrical Engineering, University of Maryland Baltimore County, 1993.

[5] Kraut S , Scharf L L . The CFAR adaptive subspace detector is a scale-invariant GLRT[C]// IEEE Sp Workshop on Statistical Signal & Array Processing. IEEE, 2002:57-60.

[6] DENG Shi-jie,WANG,WANG Hai- yan,XU An,GAO Chun-qing,LI Jun-bing. Target Detection Method Based on Antigrowth [J].Acta Optica Sinica,2022,42(02):88-98.

[7] Harsanyi J C , Chang C I . Hyperspectral image classification and dimensionality reduction: an orthogonal subspace projection approach[J]. IEEE Trans.geosci. & Remote Sensing, 1994, 32(4):779-785.

[8] Wen M X.Research on Hyperspectral Moving Target Detection Method in Complex Background Clutter[D].University of Chinese Academy of Sciences,2019.

[9] Reed I S , Yu X . Adaptive multiple-band CFAR detection of an optical pattern with unknown spectral distribution[J]. IEEE Transactions on Acoustics, Speech, and Signal Processing, 1990, 38(10):P.1760-1770.

[10] Yu X , Reed I S . Comparative performance analysis of adaptive multispectral detectors[J]. IEEE Transactions on Signal Processing, 1993, 41(8):P.2639-2656.

[11] Zhang B, Gao L R. Hyperspectral Image Classification and Target Detection. [M]Beijing: Science Press, 2011.

[12] Qian D , Ren H . Performance analysis for CEM and OSP[J]. Proc Spie, 2002, 4725:501-508.

[13] Chang C I , Chiang S S . Anomaly detection and classification for hyperspectral imagery[J]. IEEE Transactions on Geoscience and Remote Sensing, 2002, 40(6):1314-1325.

[14] Hsueh M , Chang C I . Adaptive causal anomaly detection for hyperspectral imagery[C]// Geoscience and Remote Sensing Symposium, 2004. IGARSS '04. Proceedings. 2004 IEEE International. IEEE, 2004.

[15] Kwon H , Nasrabadi N M . Kernel RX-algorithm: a nonlinear anomaly detector for hyperspectral imagery[J]. IEEE Transactions on Geoscience & Remote Sensing, 2005, 43(2):388-397.

[16] Lo E, Ingram J . Hyperspectral anomaly detection based on minimum generalized variance method[J]. Proceedings of SPIE - The International Society for Optical Engineering, 2008, 6966.

[17] Yongguang, Zhai, Lifu, et al. A Modified Locality-Preserving Projection Approach for Hyperspectral Image Classification[J]. IEEE Geoscience and Remote Sensing Letters, 2016, 13(8):1059-1063.

[18] Ren H , D Qian, Chang C I , et al. Comparison between constrained energy minimization based approaches for hyperspectral imagery[C]// IEEE Workshop on Advances in Techniques for Analysis of Remotely Sensed Data. IEEE, 2004.

[19] Chang, Chein-I. Hyperspectral Data Processing (Algorithm Design and Analysis) || Progressive Coding for Spectral Signatures[M]. 2013.

[20] Deng X , Miao F , Zhai Y , et al. Two modified target detection algorithms based on morphology for hyperspectral imagery[J]. Acta Scientiarum Naturalium Universitatis Sunyatseni, 2017.

[21] Li N, Zhao H J, Jia G R, et al.Hyperspectral image anomaly detection based on extended mathematical morphology [J] Acta optica Sinica, 2008 (08): 1480-1484.