

# A MODIFIED MULTIPLE TARGETS DETECTION ALGORITHM BASED ON EXTENDED MORPHOLOGY FOR HYPERSPECTRAL IMAGERY

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**ABSTRACT:** Proposed an improved algorithm based on Multiple-Target Constrained Energy Minimization algorithm (MCEM). 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 autocorrelation matrix, efficiently reduced the interference of targets. This algorithm makes full use of the shape and value of spectral vector, while acquiring the size and spectrum of targets, to calculate the cumulative distance between targets and each sample pixel within an window which bigger than targets' size and then displace the whole pixels in this window with the pixel which has the biggest cumulative distance. By moving the window to go through the whole image, we eliminated all the targets in the image as far as possible and got an accurate background information. This paper validated the proposed algorithm by simulated image, which, with the Three Dimensional Operational Characteristics Curve, indicated that the proposed algorithm, compared to the original algorithm, reduced false alarm effectively and improved detection accuracy.

## 1. INTRODUCTION

Hyperspectral target detection makes full use of continuous reflectance spectrum, which can represent the property of substance<sup>[1]</sup>, of hyperspectral image to differentiate targets and background. There are various algorithms developed in recent 20 years in this field. Such as signal theory based Constrained Energy Minimization (CEM)<sup>[2]</sup>, linear mixture model and subspace model based Orthogonal Subspace Projection(OSP)<sup>[3]</sup> and anomaly detection algorithms, RXD、UTD and LPTD[4]. 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<sup>[4]</sup>; 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 is not necessarily the target of interest. Harsanyi proposed CEM algorithm which only needs the spectrum of targets to solve the problems above. But it has evidenced that CEM is very sensitive to noise and it cannot classify the same type of targets with similar signatures. In order to solve this problem, Chein-I Chang et al considered general approaches, Multiple-Target CEM (MCEM), Sum CEM(SCEM) and Winner-Take-All CEM (WTACEM)<sup>[5]</sup>. Those general approaches can not only solve CEM's sensitivity to target spectrum, but also break through the limitation of single target detection. But, similar with CEM, those approaches also ignore the impact of target on the background statistics. Considering the same way of thinking and similar formula form between CEM and MCEM, this paper proposed an improved algorithm using extended morphology method to address this problem of MCEM. In addition, this paper employs 3D ROC (three dimensional receiver operation characteristics) curves to assess the detection accuracy, which can overcome the shortcoming of 2D ROC.

## 2. METHODOLOGY

### 2.1 Proposed algorithm

The equation of MCEM algorithm<sup>[3]</sup> is given by:

$$D_{MCEM}(x_i) = \frac{x_i^T R^{-1} D}{D^T R^{-1} D} * 1 \quad (\text{Equation 1})$$

Where  $R = \frac{1}{N} \sum_{i=1}^N x_i x_i^T$  turns out to be the sample autocorrection matrix of hyperspectral image,

$D = \{d_1, d_2, d_3, \dots, d_q\}$  is a desired signature matrix consisting of q signatures of interest,  $d_1, d_2, d_3, \dots, d_q$ , T denotes transpose operator, 1 is a  $p \times 1$  column constraint vector with ones in all components. Conspicuously, MCEM, in case of no information of background, evaluated the approximate background information by information of whole image. That is, R includes the autocorrection matrix of targets.

In order to eliminate the autocorrelation matrix of targets in  $R$ , this paper uses orthogonal projection divergence based morphological erode operator, which removes the targets first, to extract the information of background. Firstly, we define a structure element with a size bigger than the size of target. And then the cumulative distance of pixel(x, y) and targets is given by:

$$D[f(\mathbf{x}, \mathbf{y})] = \left\{ \sum_s \sum_t \text{distance}[f(\mathbf{x}, \mathbf{y}), f(\mathbf{s}, \mathbf{t})] | (\mathbf{x}, \mathbf{y}) \in D_f, (\mathbf{s}, \mathbf{t}) \in D_b \right\} \quad (\text{Equation 2})$$

Where  $D_f$  and  $D_b$  denote domain of hyperspectral image and targets respectively, *distance* denotes the linear distance between two pixel vector. We calculate this distance using orthogonal projection divergence which based on orthogonal subspace projection theory.

$$\text{distance} = \text{OPD}(\mathbf{x}_i, \mathbf{x}_j) = \left( \mathbf{x}_i^T \mathbf{P}_{x_j}^\perp \mathbf{x}_i + \mathbf{x}_j^T \mathbf{P}_{x_i}^\perp \mathbf{x}_j \right)^{\frac{1}{2}} \quad (\text{Equation 3})$$

Where  $\mathbf{P}_{x_m}^\perp = \mathbf{I}_{L \times L} - \mathbf{x}_m (\mathbf{x}_m^T \mathbf{x}_m)^{-1} \mathbf{x}_m^T$ ,  $m=i, j$  and  $\mathbf{I}_{L \times L}$  is unit matrix with  $L \times L$  dimension.  $\mathbf{P}_{x_m}^\perp$  denotes the projection matrix of space which orthogonal to  $x_m$ . Obviously, OPD method, which uses the value and the shape of pixel vector, can differentiate two vectors well [6].

After calculating the cumulative distance of all pixels within structure element, we find the pixel with the longest cumulative distance and replace all the pixels with this pixel. The erode operator which find the longest cumulative distance is given by:

$$\text{erode}(\mathbf{x}, \mathbf{y}) = (f - b)(\mathbf{x}, \mathbf{y}) = \text{Max} \left( D[f(\mathbf{x} + \mathbf{s}, \mathbf{y} + \mathbf{t}), b] \right) \quad (\text{Equation 4})$$

And then move the structure element and do the same work in the structure element, when the structure element go through the whole image we get the background information B. now, we can calculate the background autocorrelation matrix  $R^*$  precisely. The formula of proposed algorithm is given by:

$$D_{\text{morMCEM}}(\mathbf{x}_i) = \frac{\mathbf{x}_i^T (\mathbf{R}^*)^{-1} \mathbf{D}}{\mathbf{D}^T (\mathbf{R}^*)^{-1} \mathbf{D}} * \mathbf{1} \quad (\text{Equation 5})$$

## 2.2 Accuracy evaluation method

Traditional detection accuracy estimation method is 2D ROC, which compares the performance of two detectors by the area under the curve (AUC), shown in figure 4(2). But on some occasions, two detectors may generate two different 2D ROC curves but have the same area, In this case, 2D ROC is not practical [7]. Figure 4(1) shows a new comprehensive evaluation method, referred as 3D ROC, which considers the relationships, shown in Figure 4(3)-(4), between threshold T and its derivatives, detection rate and false alarm. So the AUC of Figure 4(2) – (4) denote 2D detection rate, detection rate and false alarm.

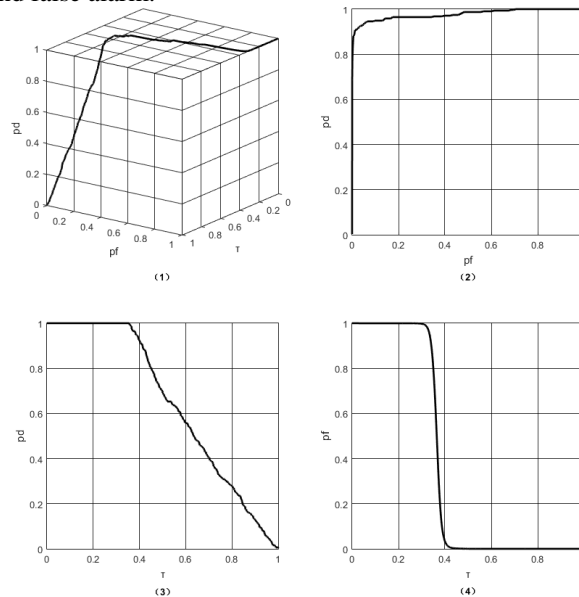
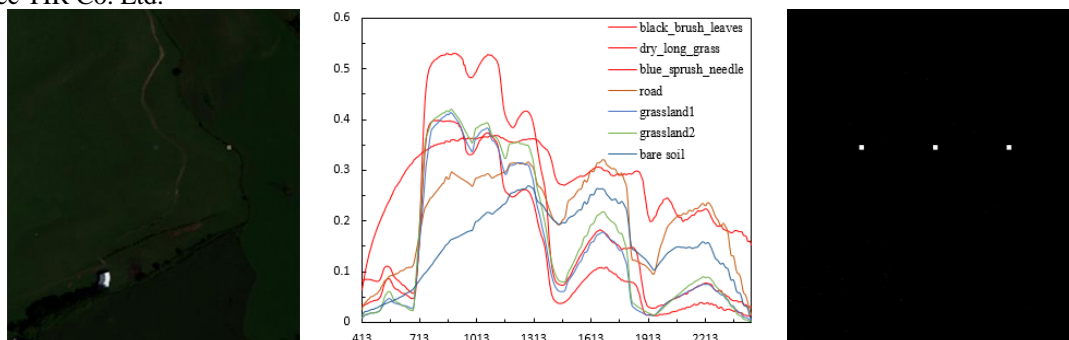


Figure1 three dimensional receiver operation characteristics curve

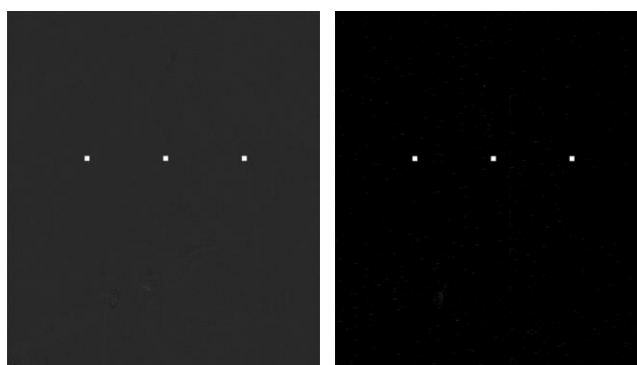
## 3. EXPERIMENT AND ANALYSIS

In order to validate this algorithm quantitatively, we implant three plants' spectrum coming from spectral library of ENVI software into true hyperspectral image to simulate a hyperspectral image. The real hyperspectral data is American Rochester Airborne Hyperspectral Data collected by the Digital Image and Remote Sensing Laboratory and Spec TIR Co. Ltd.



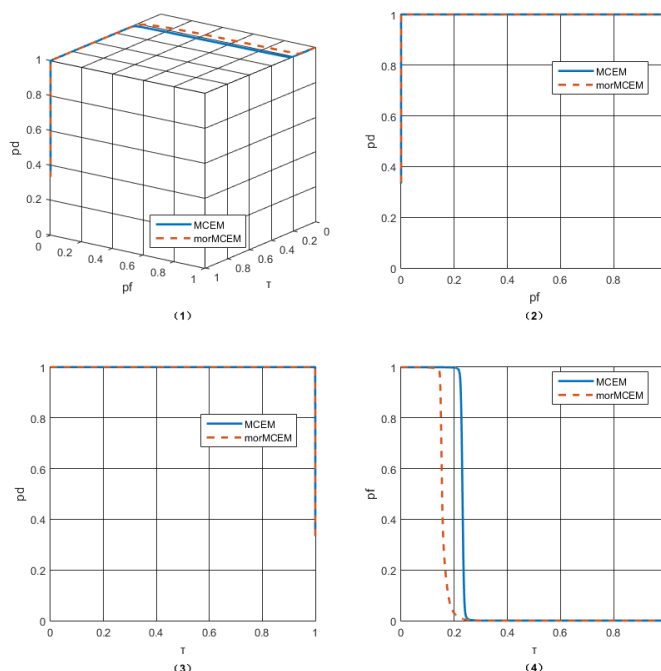
**Figure2** simulated image(left)/ its spectra (middle, red line is target spectra) and distribution of targets(right) (Target is blue\_sprush\_needle、dry\_long\_grasss and black\_brush\_leaves from left to right )

We exploited MCEM and morMCEM algorithm to detect the targets respectively, the detection result image appears as shown below, which was stretched by minimum-maximum linear method.



**Figure3** detection results of MCEM (left) and morMCEM(right)

Figure 3 shows that both MCEM and morMCEM algorithms can detect the targets smoothly with high detection accuracy. Figure 6 shows that the area of 2D ROC and detection rate are 100% but morMCEM algorithm can furtherly suppress the background value compared with MCEM algorithm. That is, the false alarm rate of morMCEM is lower.



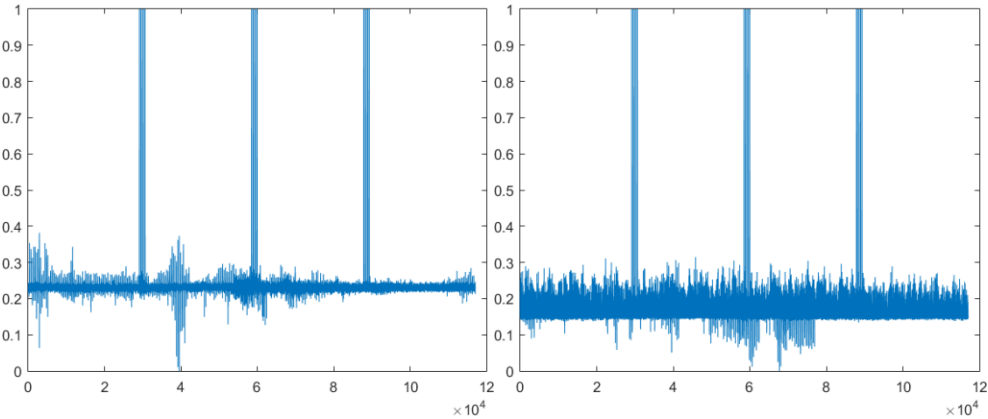
**Figure4** 3D ROC curves analysis of the detection result of algorithm based on morphology

The detection accuracy including 2D detection rate/detection rate and false alarm rate of the two algorithms are shown in Table 1 as below.

**Table1** accuracy of detection result of algorithm based on morphology

algorithm	2D detection rate	detection rate	false alarm rate
MCEM	100%	100%	23.43%
morMCEM	100%	100%	15.93%

To describe the superiority of morMCEM algorithm graphically, we use pixels of result image as X-axis and the detection value of pixels as Y-axis to display, shown as figure 7, every pixel's detection value.



**Figure 5** detection statistics of MCEM(left) and morMCEM(right)

Figure 5 shows that two algorithm's detection rate of three targets are 100%. The background values detected by morMCEM algorithm are mainly distributed around 0.15 while the background values detected by morMCEM algorithm are mainly distributed around 0.23.

#### 4. CONCLUSION

As for the shortcoming of evaluating background's information of MCEM algorithm, this paper proposed a modified method using extended morphology and evaluated the detection result using 3D ROC, which can compare the superiority between algorithms comprehensively. The experiment results show that the modified algorithm reduced the false alarm rate, so it improved the detection efficiency.

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