FAST REAL-TIME TARGET DETECTION VIA TARGET-ORIENTED BAND SELECTION

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ABSTRACT

Real-time target detection requires immediate decision-making. For fast implementation of the entire detection process, offline band selection is applied. Because target signature is usually the only prior knowledge before running causal real-time detectors, traditional band selection methods based on statistics of the entire data set cannot be used before detection. This paper develops a band selection method based on target spectrum alone, extracting bands that can preserve main features of the target. It is expected that the selected bands can remain the detection accuracy unchanged and speed up the detection process. To substantiate the utility of proposed method, causal real-time constrained energy minimization (RT-CEM) is tested on a real hyperspectral data set for experiments.

***Index Terms*—** Real-time detection, band selection, curve fitting, dimensionality reduction

1. INTRODUCTION

A real-time target detector processes hyperspectral data pixel by pixel or line by line. It updates background statistics recursively in a causal progressive manner [1]. For online detectors like causal real-time constrained energy minimization (RT-CEM) [1], the data sample with full bands is often the input. The curse of dimensionality still exists, resulting in high computational complexity of data processing.

In order to speed up real-time detection process, dimensionality reduction is in need. However, present dimensionality reduction methods [2, 3, 4] transform the data onto a low-dimensional space or select subset of original bands, which cost much time and require background statistics of the entire data set. For causal RT-CEM with only target signature provided, the background information is not known before detection. If dimensionality reduction is conducted online while detecting targets, the time delay is intolerable. If done offline before detection, the background information is not given.

This paper proposes an band selection method based on only the target signature to implement fast real-time target detection. New sample vectors are formed right after being collected according to the selected bands. Using the dimensionality reduced sample vector as the input of causal RT-CEM, we improve the computational performance significantly. This band selection method focuses on remaining the waveform of the target spectrum, keeping main features of the target. Through curve fitting for the discrete reflectance spectral points, bad bands are eliminated in that they contribute less in reconstructing the target spectrum. The work of this paper reduces time consumption significantly in data processing and meanwhile maintains detection accuracy unchanged.

2. METHODOLOGY

2.1. Causal real-time CEM

Let $\{\boldsymbol{r}_i\}_{i=1}^{n}$ be the entire data set including n samples that an imaging spectrometer has received. $\boldsymbol{r}_i = (r_{i1}, r_{i2}, \ldots, r_{iL})^T$ denotes the $\boldsymbol{L} \times 1$ sample spectral vector where $\boldsymbol{L}$ is the number of spectral bands. The prior knowledge for the target is specified by the spectral vector $\boldsymbol{d} = (d_1, d_2, \ldots, d_L)^T$.

According to [1], suppose $\boldsymbol{r}_n$ is the input data sample newly coming in, causal real-time CEM can be expressed by:

$$y = D_{CEM}(\boldsymbol{r}_n) = \frac{\boldsymbol{r}_n^T \boldsymbol{R}^{-1}(n)\boldsymbol{d}}{\boldsymbol{d}^T \boldsymbol{R}^{-1}(n)\boldsymbol{d}} \tag{1}$$

where $\boldsymbol{R}(n) = (1/n)\sum_{i=1}^{n} \boldsymbol{r}_i \boldsymbol{r}_i^T$ denotes the sample correlation matrix of the data set. $\boldsymbol{R}^{-1}(n)$ can be updated recursively using $\boldsymbol{r}_n$ and $\boldsymbol{R}^{-1}(n-1)$ in light of (2).

$$\boldsymbol{R}^{-1}(n) = \boldsymbol{R}_{n|n-1} - \frac{\boldsymbol{R}_{n|n-1}\boldsymbol{r}_n \boldsymbol{r}_n^T \boldsymbol{R}_{n|n-1}}{n + \boldsymbol{r}_n^T \boldsymbol{R}_{n|n-1}\boldsymbol{r}_n} \tag{2}$$

where $\boldsymbol{R}_{n|n-1} = [(1-1/n)\boldsymbol{R}(n-1)]^{-1}$.

2.2. Band selection via curve fitting

Due to the fact that only the target signature is given in causal RT-CEM, the proposed band selection method is based on the target spectrum alone. Considering that main features of a spectral curve are determined by absorption characteristics, reflectance spectrum at absorption regions should be representative of the target. Firstly we found the absorption regions through continuum removal (CR). In general, the spectral curve of a target owns a distinctive waveform. Using mathematic functions to fit the discrete data points could keep the waveform constant. Here, the band selection method is derived from curve fitting theory.

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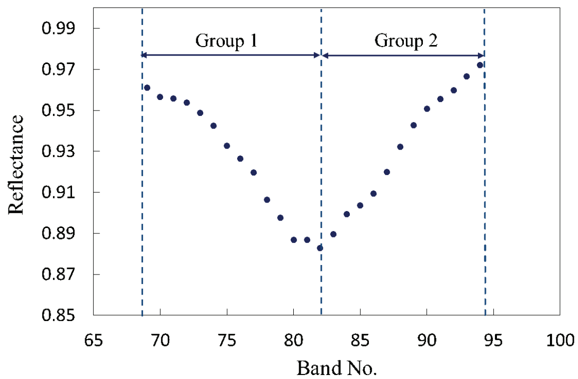


Fig. 1: Spectral absorption region after CR.

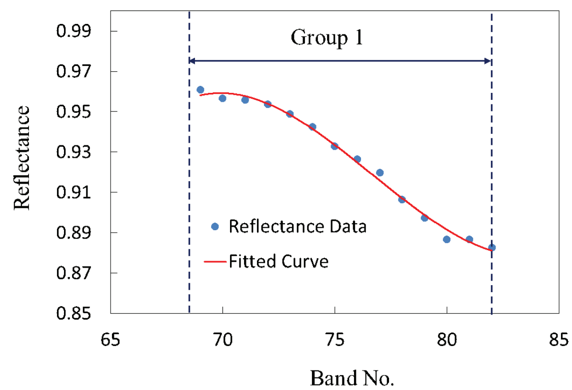


Fig. 2: Curve fitting for reflectance data points.

b_1	b_2	⋯	b_j	⋯	b_k	⋯	b_l	⋯	b_M
δ_1	δ_2	⋯	δ_j	⋯	δ_k	⋯	δ_l	⋯	δ_M

(a)

b_2	b_j	b_k	b_l	⋯
r_2	r_j	r_k	r_l	⋯

(b)

Fig. 3: Residual at (a) original bands, and (b) selected bands.

Curve fitting is the process to build an approximate curve or function which has the best fit to a series of discrete points [5]. To fit the points more accurately, data points in absorption regions are selected after CR at first and then the absorption region is divided into two parts as illustrated in Fig. 1, allowing for the asymmetry of the spectral curve.

Suppose that data points in group 1 are specified by $(\boldsymbol{b}_i, \boldsymbol{r}_i)_{i=1}^{M}$, where $\boldsymbol{b}_i$ is the band number, $\boldsymbol{r}_i$ is the corresponding reflectance and M is the number of points for fitting. Using the n^{th} degree polynomial to fit $(\boldsymbol{b}_i, \boldsymbol{r}_i)_{i=1}^{M}$, we have $f(\boldsymbol{b}_i)$ specified by

$$f(\boldsymbol{b}_i) = \boldsymbol{a}_1 \boldsymbol{b}_i^n + \boldsymbol{a}_2 \boldsymbol{b}_i^{n-1} + \cdots + \boldsymbol{a}_n \boldsymbol{b}_i + \boldsymbol{a}_{n+1} \qquad (3)$$

where$f(\boldsymbol{b}_i)$ is the corresponding function value at band $\boldsymbol{b}_i$, $\{\boldsymbol{a}_i\}_{i=1}^{n+1}$ are coefficients that can be solved by linear least squares method. This method focuses on finding the minimum of $\boldsymbol{J}(\boldsymbol{a}_1, \boldsymbol{a}_2, \ldots, \boldsymbol{a}_{n+1})$:

$$\boldsymbol{J}(\boldsymbol{a}_1, \boldsymbol{a}_2, \ldots, \boldsymbol{a}_{n+1}) = \sum_{i=1}^{M} \delta_i^2 = \sum_{i=1}^{M} [f(\boldsymbol{b}_i) - \boldsymbol{r}_i]^2 \qquad (4)$$

where $\delta_i = |f(\boldsymbol{b}_i) - \boldsymbol{r}_i|$ is called fitting residual at band $\boldsymbol{b}_i$. The coefficients $\{\boldsymbol{a}_i\}_{i=1}^{n+1}$ can be solved using partial first derivative of $\boldsymbol{J}$ as following:

$$\frac{\partial \boldsymbol{J}}{\partial \boldsymbol{a}_k} = 0 \quad (k = 1, 2, \ldots, n+1) \qquad (5)$$

By virtue of $\{\boldsymbol{a}_i\}_{i=1}^{n+1}$, we have the fitted curve $f(\boldsymbol{b}_i)$, which is plotted in Fig. 2 in red solid line. It is clearly demonstrated in Fig. 2 that the fitted curve performs quite well on keeping the waveform of the original spectrum unchanged.

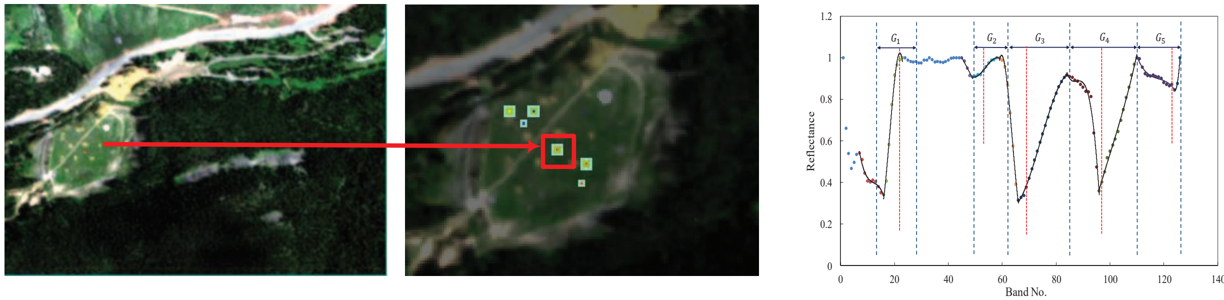
2.3. Criteria to select bands and fast detection

This band selection strategy focuses on finding data points that can reconstruct the waveform of the target spectrum. The residual δ_i of selected points should be as small as possible. In light of the fitting theory, a n^{th} degree polynomial requires at least $(n+1)$ points for curve fitting. Assume that the residuals $\{\delta_i\}_{i=1}^{M}$ are obtained after curve fitting, sort data points in each sub-group, in ascending order, according to the value of $\{\delta_i\}_{i=1}^{M}$. Then select the top $(n+1)$ points in each sub-group and label the corresponding band number $\boldsymbol{b}_i$. As shown in Fig. 3, all labeled bands $\boldsymbol{b}_i$ are extracted from the original sample vector and their corresponding reflectance data $\boldsymbol{r}_i$ are taken to constitute a new spectral vector $\boldsymbol{r}_n^{new} = (\boldsymbol{r}_1, \boldsymbol{r}_j, \boldsymbol{r}_k, \boldsymbol{r}_l, \ldots)^T$.

For fast implementation of (1) and (2), each time a new data sample $\boldsymbol{r}_n$ comes in, construct $\boldsymbol{r}_n^{new}$ according to the bands subset and then replace $\boldsymbol{r}_n$ with $\boldsymbol{r}_n^{new}$ as the input. It is clear that online construction of the new data sample vector $\boldsymbol{r}_n^{new}$ can be finished in an extremely short period of time, which will not affect the computatinal performance of real-time target detection.

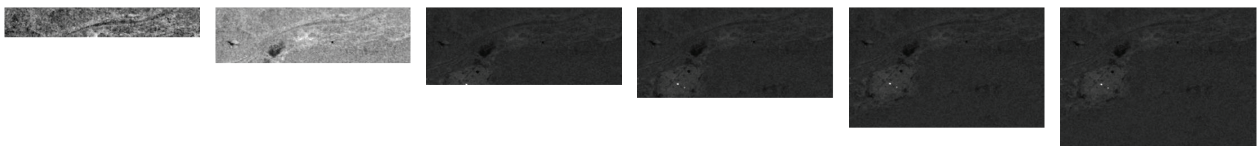
3. EXPERIMENTAL RESULTS

The used 126-band data set shown in Fig. 4a is a subscene of 350 × 250 pixels cropped from a hyperspectral image provided by the Target Detection Blind Test project [6]. It was acquired by HyMap, with the wavelengths range of 0.4 µm to 2.5 µm and the ground resolution of 3 m. The area covered by the image is Cooke City in Montana, USA. A fabric panel target with prior spectral knowledge in the red box was

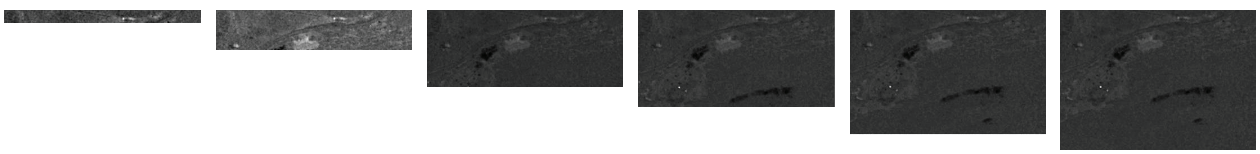


(a) (b)

Fig. 4: HyMap dataset: (a) true color scene, (b) target spectrum after CR with fitted curve.



(a)



(b)

Fig. 5: Detection maps produced by (a) original bands, (b) a subset of original bands.

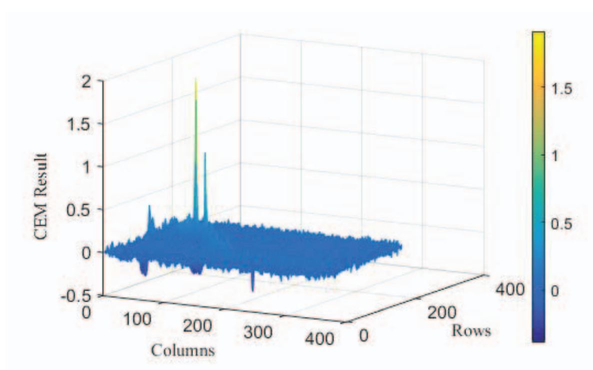


Fig. 6: 3-D representation of the detection map produced by original bands.

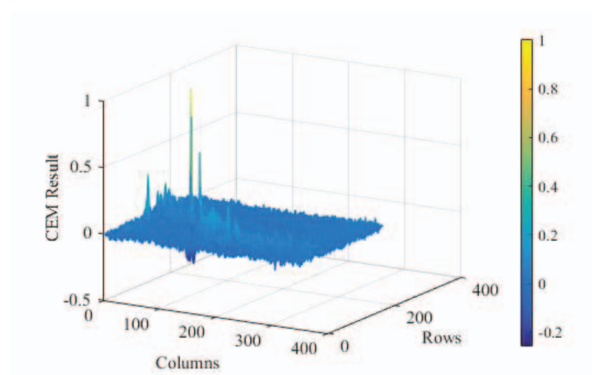


Fig. 7: 3-D representation of the detection map produced by a subset of original bands.

deployed in this area. The reflectance spectrum of the target after CR and its fitted curve are plotted in the form of discrete data points in Fig. 4b.

As illustrated in Fig. 4b, five absorption spectral groups $\{\boldsymbol{G}_i\}_{i=1}^{5}$ are found. In order to fit the data points more accurately, each group is divided into 2 sub-groups by red dashed line as shown in Fig. 4b. Here, a second or third degree polynomial can fit the points of each sub-group well. The fitted curve in each group is plotted in black solid line in Fig. 4b. Using the strategy proposed in Sect. 2.3, 39 bands are selected as the subset. For an incoming data sample with 126 bands, a new data sample vector is formed, using the 39 selected bands, to be the input of RT-CEM. Fig. 5 show the pixel-by-pixel detection maps produced by using all bands and the

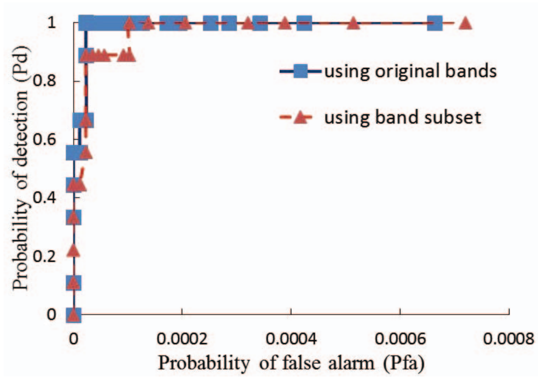


Fig. 8: ROC curves produced by RT-CEM using original bands and its subset.

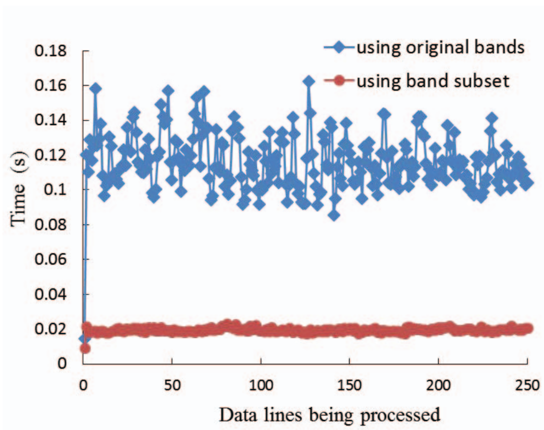


Fig. 9: Computer processing time of RT-CEM.

subset. The 3-dimension representation of the detection results are illustrated in Fig. 6 and 7, where the target is well picked up.

For further quantitative analysis of the detection performance, the receiver operating characteristics (ROC) curves is used as demonstrated in Fig. 8. The accuracy remains approximately unchanged when using selected bands.

The computer environments used for this experiment were a 64-bit windows 7 operating system with AMD X4-750 Quad Core Processor, CPU of 3.4 GHz and 4 GB of RAM. Matlab is used for simulation. Fig. 9 shows the computer processing time of causal RT-CEM when using full bands and its subset. The time cost on target detection is reduced significantly when using selected bands. Overall, the proposed band selection method gives a way to implement fast causal real-time target detection.

4. CONCLUSION

In this paper, we developed a novel target-oriented band selection method to speed up the process of real-time target detection. Through curve fitting for the target spectrum, main features of the target are well remained. It is an appropriate method for online dimensionality reduction with no background data involved in. Thus the computational performance of real-time detection will not be affected by band selection. Due to the fact that the fitted curve is particularly matched with the waveform of the target spectrum, the detection performance is not degraded. More importantly, the computational performance of real-time detection is promoted significantly. Finally, the proposed method contributes to hyperspectral data compression in that the high-dimensional hyperspectral sample vector can be represented by a few featured bands.

5. REFERENCES

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