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Multiple Object Detection in Hyperspectral Imagery Using Spectral Fringe-Adjusted Joint Transform Correlator

Paheding Sidike
University of Dayton

Vijayan K. Asari
University of Dayton, vasari1@udayton.edu

Mohammad S. Alam
University of South Alabama

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Paheding Sidike[a], Vijayan K. Asari[a], Mohammad S. Alam[b]
[a]Dept. of Electrical and Computer Engineering, University of Dayton, OH, USA 45469;
[b]Dept. of Electrical and Computer Engineering, University of South Alabama, AL, USA 36688

ABSTRACT

Hyperspectral imaging (HSI) sensors provide plenty of spectral information to uniquely identify materials by their reflectance spectra, and this information has been effectively used for object detection and identification applications. Joint transform correlation (JTC) based object detection techniques in HSI have been proposed in the literatures, such as spectral fringe-adjusted joint transform correlation (SFJTC) and with its several improvements. However, to our knowledge, the SFJTC based techniques were designed to detect only similar patterns in hyperspectral data cube and not for dissimilar patterns. Thus, in this paper, a new deterministic object detection approach using SFJTC is proposed to perform multiple dissimilar target detection in hyperspectral imagery. In this technique, input spectral signatures from a given hyperspectral image data cube are correlated with the multiple reference signatures using the class-associative technique. To achieve better correlation output, the concept of SFJTC and the modified Fourier-plane image subtraction technique are incorporated in the multiple target detection processes. The output of this technique provides sharp and high correlation peaks for a match and negligible or no correlation peaks for a mismatch. Test results using real-life hyperspectral data cube show that the proposed algorithm can successfully detect multiple dissimilar patterns with high discrimination.

Keywords: Hyperspectral imaging, object detection, joint transform correlation, fringe-adjusted filter, spectral signature, correlation, class-associative filter

1. INTRODUCTION

Hyperspectral imaging (HSI) detection algorithm can be generally classified into stochastic and deterministic approaches [1]. Deterministic approaches are comparatively simple to apply since it does not require the statistical information of the targets and background classes. Some popular deterministic algorithms, such as spectral angle mapper (SAM) [2] and spectral fringe-adjusted joint transform correlation (SFJTC) based techniques [3-6], have been used for hyperspectral image processing. Specifically, the decision criterion of the SAM is based on the similarity of the angle between two spectral vectors, while the SFJTC determines a desired target by analyzing the correlation peak intensity between an unknown spectral signature and a known reference spectrum. Compared to the SAM, the SFJTC technique is able to accommodate noise and variations of the spectral signatures. However, both SAM and SFJTC techniques were designed to detect only similar patterns in constant time using hyperspectral information. Although the joint transform correlation (JTC) based dissimilar pattern detection algorithms from two-dimensional image have been introduced in literatures [7-9], but HSI based multiple dissimilar target detection using SFJTC is yet to be done. Thus, in this paper, we propose a class-associative correlation based SFJTC technique for detecting a class of objects consisting of dissimilar patterns.

In our proposed algorithm, input spectral signatures from a given hyperspectral image data cube are correlated with multiple reference signatures using class-associative technique [10]. To achieve better correlation output, the concept of SFJTC and the modified Fourier-plane image subtraction technique [11] are incorporated in the multiple target detection processes. The output of this technique provides sharp and high correlation peaks for a match and negligible or no correlation peaks for a mismatch. In detail, if there are dissimilar patterns present in the scene, the proposed algorithm yields distinctive correlation peak for each target simultaneously without losing inherent advantage of the SFJTC and class-associative filtering. Similar to some deterministic target detection approaches, it also does not need

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any training step in priori, whereas in many statistical machine learning techniques, the reference signature and none-target information are required before performing target recognition process. Furthermore, the decision matrix such as peak-to-clutter mean (PCM) is also integrated in the algorithm which makes the performance of the proposed technique is highly based on the signature of the target but not the amplitude. This also enable the proposed algorithm intensity invariant since the reflectance information of a material is usually preserved in hyperspectral imagery whereas the intensity may change due to variable environment [3]. The feasibility of the proposed technique has been tested using real-life hyperspectral imagery. Test results show that the proposed algorithm can successfully detect multiple dissimilar targets while satisfying the equal correlation peak criteria by adjusting parameters in the class-associative JTC filter formulation, such that it will be an excellent candidate of a pattern recognition technique in HIS.

The rest of paper is organized as follows. Section 2 reviews the SFJTC detection algorithm and provides formulation of the proposed scheme. In section 3, test results are presented and discussed. Finally, section 4 outlines concluding remarks and future research direction in this technology.

2. METHODOLOGY

The following subsections will give a brief review of the SFJTC technique, and then introduce the proposed SFJTC based multiple object recognition scheme.

2.1 Spectral fringe-adjusted joint transform correlation

In SFJTC, the reference spectral signature $r(y)$ is known a priori, which can be simulated or obtained from laboratory measurement. The unknown input spectral signature $s(y)$ is formed by taking reflectance value of a single pixel values in each spectra band in input hyperspectral dataset. $r(y)$ and $s(y)$ are separated by a distance $2y_0$ along the x-axis. The input joint spectral signature $f(y)$ can be expressed as [3]

$$f(y) = r(y + y_0) + s(y - y_0). \tag{1}$$

Applying the Fourier transform to Eq. 1, yields,

$$F(u) = |R(u)|\exp[j\phi_r(u) + juy_0] + |S(u)|\exp[j\phi_s(u) - juy_0], \tag{2}$$

where $|R(u)|$ and $|S(u)|$ are the amplitude; $\phi_r(u)$ and $\phi_s(u)$ are the phases of the Fourier transform of $r(y)$ and $s(y)$, respectively; and u is a frequency-domain variable. The corresponding joint power spectrum (JPS) may be calculated by

$$\begin{aligned} |F(u)|^2 \ = \ & |R(u)|^2 \ + \ |S(u)|^2 + |R(u)||S(u)|^* \\ & \times \ \exp[j\{\phi_r(u) - \phi_s(u) + 2uy_0\}] + |R(u)|^*|S(u)| \\ & \times \exp[j\{\phi_s(u) - \phi_r(u) - 2uy_0\}]. \end{aligned} \tag{3}$$

where $|R(u)|^2$ and $|S(u)|^2$ are the autocorrelation components of $r(y)$ and $s(y)$, respectively; and the last two terms are the cross-correlation components between the reference and input signatures. The autocorrelation components introduces false alarms to the system, thus the Fourier plane image subtraction technique is used, where the power spectrum of the input signature and the reference signature are subtracted from the JPS shown in Eq. (3). This resultant in the modified JPS, expressed as [3]

$$\begin{aligned} |P(u)|^2 \ = \ & |F(u)|^2 - |R(u)|^2 - \ |S(u)|^2 = \ |R(u)||S(u)|^* \\ & \times \exp[j\{\phi_r(u) - \phi_s(u) + 2uy_0\}] + \ |R(u)|^*|S(u)| \\ & \times \exp[j\{\phi_s(u) - \phi_r(u) - 2uy_0\}]. \end{aligned} \tag{4}$$

The performance of the correlation output can be further improved by multiplying the modified JPS with fringe-adjusted filter (FAF) before the final inverse Fourier transform. The FAF is characterized by the transfer function defined as [12],

$$H(u) = \frac{B(u)}{A(u) + |R(u)|^2} \tag{5}$$

where $A(u)$ and $B(u)$ are either constants or functions of u. When $B(u) = 1$ and $|R(u)|^2 \gg A(u)$, the FAF becomes a perfect inverse filter. Then the JPS in Eq. (4) is multiplied by $H(u)$ to yield the fringe-adjusted JPS, which is given by

$$G(u) = H(u) \times |P(u)|^2, \tag{6}$$

Finally, an inverse Fourier transform of the $G(u)$ yields the correlation output as:

$$c(x) = F^{-1}\{H(u) \times |\mathrm{P}(u)|^2\}. \tag{7}$$

Afterwards, a post-processing is performed on the correlation output in Eq. (7) to achieve more distinguishable peaks for each detected target in hyperspectral data cube as described in [3].

2.2 Class-associative multiple target detection using SFJTC

In this section, a class-associative filter based SFJTC will be introduced. The key of using the class-associative filter is to detect single or multiple non-identical targets. Figure 1 shows block diagram of the proposed algorithm.

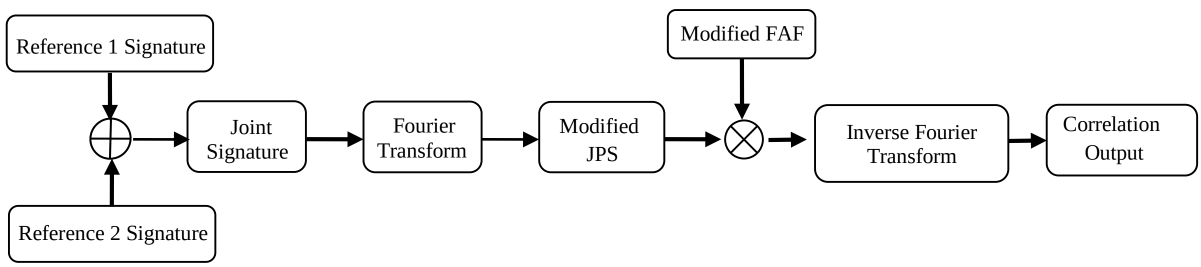


Fig.1. Block diagram of the proposed pattern recognition scheme.

Consider two known dissimilar objects have two unique spectral signatures, denoted as $r_1(y)$ and $r_2(y)$, respectively. Let $s(y)$ be a unknown input spectral signature from a hyperspectral dataset, then four input joint signatures using $r_1(y)$ and $s(y)$ can be obtained as follow,

$$f_{11}(y) = r_1(y + y_0) + s(y - y_0) \tag{8}$$

$$f_{21}(y) = r_1(y + y_0) - js(y - y_0) \tag{9}$$

$$f_{31}(y) = r_1(y + y_0) - s(y - y_0) \tag{10}$$

$$f_{41}(y) = r_1(y + y_0) + js(y - y_0) \tag{11}$$

Similarly, using $r_2(y)$ and $s(y)$, another four input joint spectral signatures are generated by

$$f_{12}(y) = r_2(y + y_0) + s(y - y_0) \tag{12}$$

$$f_{22}(y) = r_2(y + y_0) - js(y - y_0) \tag{13}$$

$$f_{32}(y) = r_2(y + y_0) - s(y - y_0) \tag{14}$$

$$f_{42}(y) = r_2(y + y_0) + js(y - y_0) \tag{15}$$

(a)

(b)

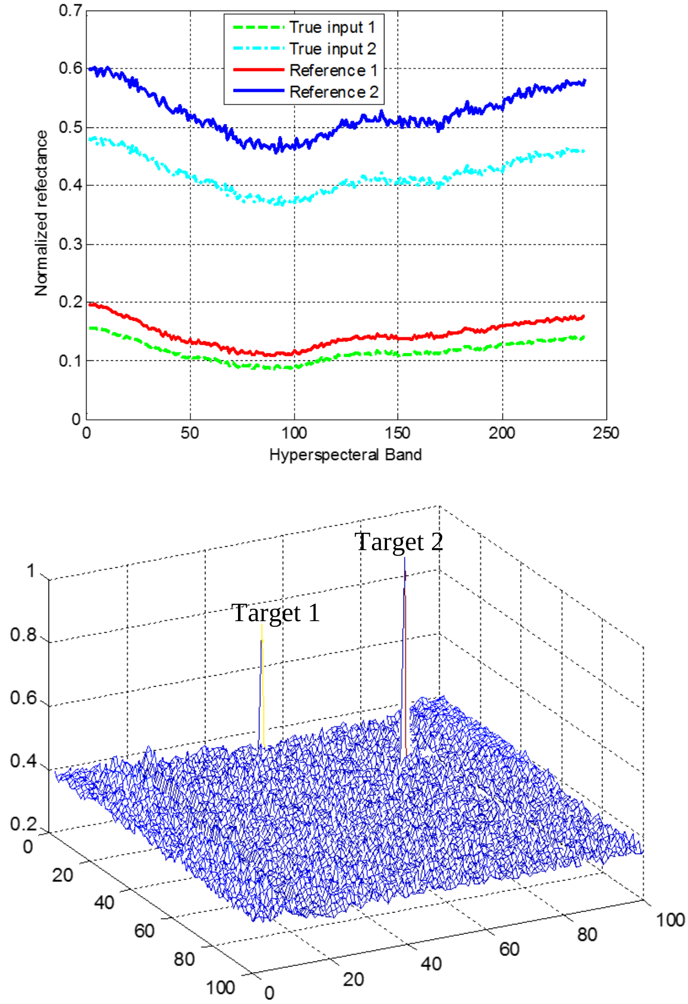


Fig.2. (a) References and true inputs, and (b) 3D correction output corresponding to (a).

The joint power spectra corresponding to Eqs. (8) – (15), can be computed by

$$T_{i1} = |F_{i1}|^2, \quad i = 1,\ 2, 3, 4 \tag{16}$$

$$T_{i2} = |F_{i2}|^2, \quad i = 1,\ 2, 3, 4 \tag{17}$$

where F_{11}, F_{21}, F_{31}, F_{41}, F_{12}, F_{22}, F_{32} and F_{42} are the Fourier transform of f_{11}, f_{21}, f_{31}, f_{41}, f_{12}, f_{22}, f_{32} and f_{42}, respectively. Then from Eqs. (16) and (17), the modified joint power spectra is obtained by

$$P_1(u) = T_{11} + j\,T_{21} - T_{31} - j\,T_{41} \tag{18}$$

and

$$P_2(u) = T_{12} + j\,T_{22} - T_{32} - j\,T_{42} \tag{19}$$

By use of Eqs. (18) and (19), the final JPS is formulated as follow,

$$P(u) = \alpha\,P_1(u) + \beta\,P_2(u) \tag{20}$$

where α and β are constants and satisfy $\alpha + \beta = 1$. Due to the two targets present in the scene, the FAF filter in Eq. (5) may be reformulated as

$$\widetilde{H}(u) = \frac{B(u)}{A(u) + |R_1(u)|^2 + |R_2(u)|^2} \tag{21}$$

By multiplying $\widetilde{H}(u)$ with $P(u)$, we obtain the filtered JPS, expressed as

$$\tilde{G}(u) = P(u) \times \widetilde{H}(u) = \frac{B(u)[\alpha P_1(u) + \beta P_2(u)]}{A(u) + |R_1(u)|^2 + |R_2(u)|^2} \tag{22}$$

Finally, applying an inverse Fourier transform to the $\tilde{G}(u)$ in Eq. (22) yields the correlation output. The output of this technique provides sharp and distinct PCM values when all matched target and negligible outputs for mismatched spectra.

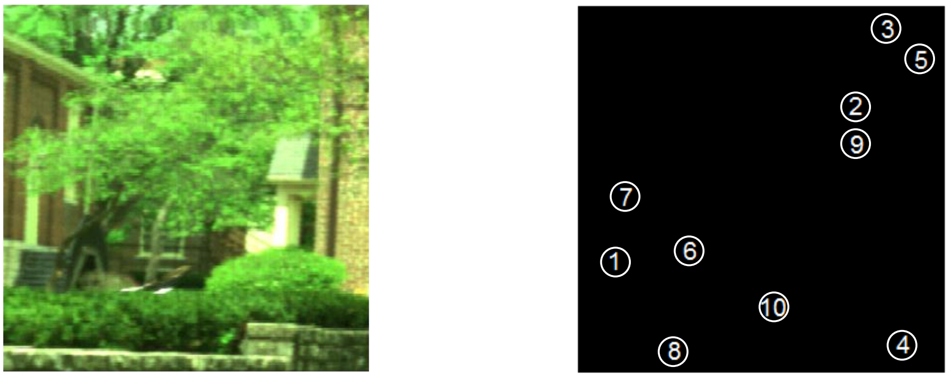
To illustrate this concept, we randomly inserted two true spectral signatures into a hyperspectral data cube and correlated them with two known reference spectral signals as shown in Fig. 2(a). Figure 2(b) shows the correlation output. From Fig. 2(b), it is obvious that the proposed algorithm yields higher PCM and detects the two dissimilar targets simultaneously without any ambiguity.

3. TEST RESULTS

In this section, the performance of the proposed technique is tested and evaluated. We use the Resonon Pika II hyperspectral camera, which provides 240 spectral channels that ranges from 400-900nm with 2.1nm spectral resolution, to capture real-life hyperspectral dataset and investigate our algorithm from two aspects: (1) input scene contains multiple similar targets, (2) input scene contains multiple dissimilar objects.

3.1 Input scene contains multiple similar targets

For evaluate the performance of the proposed algorithm for multiple similar target detection, we randomly selected ten pixels from the input hyperspectral dataset and replaced their signatures with ten simulated target signature. Figure 3(a) shows true color bands of the input hyperspectral data cube and Figure 3(b) indicates location of the inserted targets in the scene. As for the parameters in in Eqs. (20) and (21), we chose $\alpha = \beta = 0.5$, $A(u) = 10^{-3}$ and $B(u) = 1$. The corresponding correlation output is shown in Fig.4. From Fig. 4, it is evident that the proposed technique successfully detected all of the targets and rejected non-target objects.



(a) (b)

Fig.3. (a) Input scene, and (b) the locations of the inserted targets.

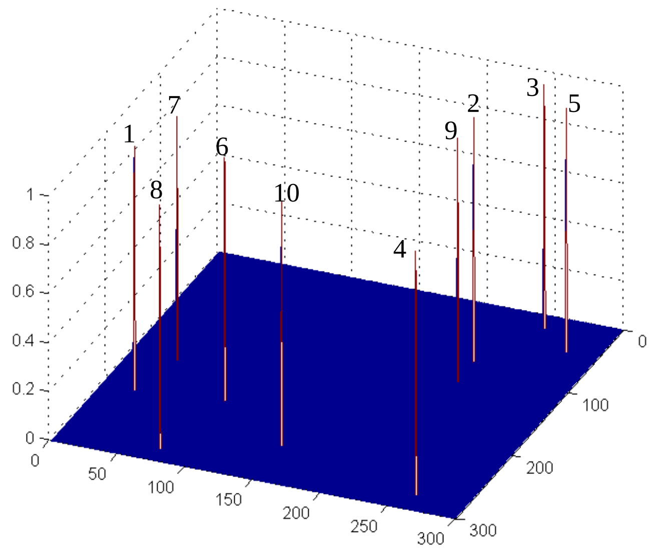
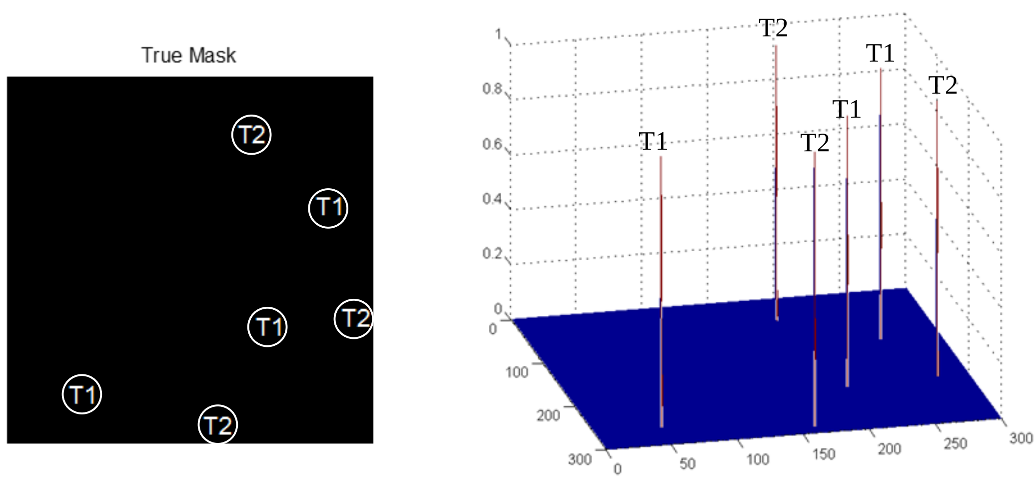


Fig.4. 3D correlation output for ten desired targets in the scene.

3.2 Input scene contains multiple dissimilar targets

To evaluate the robustness of the proposed technique for dissimilar target detection, this time we consider multiple dissimilar targets present in the input scene. To achieve this, we randomly chose six pixels from the input scene in Fig. 3(a) and replaced their signatures with six targets including two dissimilar targets with three patterns for each. Figure 5(a) is the binary truth image showing the locations of the inserted targets. The corresponding 3D detection output of the proposed algorithm is shown in Fig. 5(b). From Fig. 5(b), one can conclude that the proposed algorithm is able to detect multiple dissimilar targets simultaneously with high discriminability. In addition, in Fig. 5, although the desired peaks are clearly visible and distinct, the difference between the PCM heights of the desired targets may vary, this is due to the dissimilarity in the energy content of the reference signatures, which can be alleviated by adjusting the values of α and β. In this experiment, both of the values of α and β are set to 0.5.



(a) (b)

Fig.5. (a) Locations of the inserted targets, and (b) Correlation output for multiple targets in (a), where T1 represents locations of all target-1, and T2 indicates locations of all target-2.

4. CONCLUSION

In this paper, a new pattern recognition algorithm in hyperspectral imagery is proposed. The proposed algorithm is designed to detect a class of objects consisting of similar and dissimilar patterns. To do so, input spectra signatures from the hyperspectral image are correlated with the known multiple reference signatures and the finally output produces distinctive correlation peaks for each target and negligible peaks for non-targets. The test results show the proposed technique can successfully detect multiple objects irrespective of their similarity of the reference signatures, which verify its effectiveness.

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