Selecting Optimal Bands for Sub-pixel Target Detection in Hyperspectral Images Based on Implanting Synthetic Targets

IET Image Processing

Submitted on: 17-09-2018

Submitted by: Shahram Sharifi hashjin, Ali Darvishi Boloorani, Safa Khazai, Ataolah Abdollahi Kakroodi

Keywords: HYPERSPECTRAL IMAGE, FEATURE SELECTION, PARTICLE SWARM OPTIMISATION, GENETIC ALGORITHM, SIGNAL DETECTION
Selecting Optimal Bands for Sub-pixel Target Detection in Hyperspectral Images Based on Implanting Synthetic Targets

Shahram Sharif hashjin1, Ali Darvishi boloorani2*, Safa Khazai2 and Ata Abdollahi kakroodi1

1 Department of remote sensing and geographic information systems, College of Geography, University of Tehran, Enghelab Square, Tehran, Iran.
2 Civil Engineering Research Center, Imam Hossein Comprehensive University, Babaei Highway, Tehran, Iran.
*ali.darvishi@ut.ac.ir

Abstract: Target detection at sub-pixel abundances is in fact one of the challenging issues of hyperspectral image processing. Selection of optimal bands to improve sub-pixel target detection (STD) performance is one of the common solutions, applied by many researchers. Nevertheless, absence of sufficient training data is the main weakness of selecting optimal bands with regards to this approach. The present research introduces a new band selection method for STD in hyperspectral images, based on creating training data, in which the desired target spectrum is implanted randomly in a series of host pixels from the entire hyperspectral image. Afterward, via running an optimization algorithm twice, with the aim of minimizing the false alarm rate (FAR) in local Adaptive Coherence Estimator (ACE) target detection algorithm, the number of optimal bands and optimal spectral bands are selected. In this study, the performance of three optimization methods, including Genetic Algorithm (GA), Grey Wolf Optimization (GWO), and Particle Swarm Optimization (PSO), are compared. Experimental results on Hymap and Hyperion datasets show that, the proposed method obtains the minimum FAR compared to the rest of evaluated methods. Also, based on the results obtained, GWO outperforms GA and PSO optimization methods in the STD domain.

1. Introduction

High spectral resolution of hyperspectral images in form of very narrow and constant bands, within visible and infrared spectral ranges, has put the technology of remote hyperspectral measurement under spotlight in order to detect objects as well as earthly phenomena [1]. However, a substantial number of bands lead to heavy computational costs [2, 3] along with Hughes Effect [4] on hyperspectral image processing. Hence, in recent years much attention has been paid to reduction of computational complexity in the processing of hyperspectral images, particularly in the field of target detection [5-16]. Feature selection (of the band) and extraction are two main approaches of data dimension reduction [17]. Generally, in terms of feature extraction and particularly in relation to target detection, a part of important spectral information may become compromised and distorted through transfer process to a new space [11]. Therefore, in order to keep the physical meaning of materials spectral signature, the best choice would be to use band selection to reduce the dimension in target detection [10].

Selection of spectral bands usually occurs in two ways, namely supervised and unsupervised. Regardless of the method, band selection generally takes place in accordance with the evaluation of similarity parameters among the bands [18, 19]. So far, most band selection methods have been presented with the purpose of improving the accuracy of image classification [20, 21]; however, there is few research conducted on target detection [5]. One reason behind this is the shortage or absence of training samples of the desired target [5]. The problem is of higher account, especially when detecting sub-pixel targets, wherein the target only occupies part of a pixel surface. It should be added that in sub-pixel targets, the spectrum of the desired target is excessively under influence spectra of neighboring pixels, which makes it difficult to distinguish target pixels from non-target ones. In order to address the issue, the research selects appropriate bands for sub-pixel target detection (STD) through several simulated training samples, created by means of target spectrum implantation in the image. Recently, target implantation method has been used for creating artificial sub-pixel targets on hyperspectral images in order to investigate the performance of STD algorithms [22-25].

After achieving sufficient implanted targets as training data, searching strategy in hyperspectral image space is of high account for optimal band selection [5]. There have been various methods, whether supervised or unsupervised, which presented for band selection. The most important problems of these methods are as follows: (i) many of them are time-consuming; (ii) some cannot be employed for target detection and are useful only in the field of classification; and (iii) the rest is merely confined to one detection method. Therefore, in order to address these shortcomings, some evolutionary algorithms such as Genetic Algorithm (GA) [17, 26], Particle Swarm Optimization (PSO) [5, 27, 28] and Grey Wolf Optimization (GWO) [29] have caught researchers attention for selection of proper bands.

To make the optimization algorithms exploit well in search space, their cost functions must be well defined. In [5], selection of optimal bands for target detection has been performed by optimization algorithms. PSO has entailed the use of both maximum-submaximum-ratio (MSR) and correlation coefficient (CC) functions. These methods have some restriction in solving the problems.

Another important issue in the field of band selection is to determine the number of chosen bands. In some band selection methods, especially in the field of particle
intelligence, the number of bands had to be determined beforehand [5, 27].

This study offers a proposed method for determining the band, inspired the idea presented in [28]. The proposed method determines the number of optimal bands by running an optimization algorithm twice and creates proper training data for STD via random implantation of the target spectrum in a series of image pixels. In this study, Local ACE target detection algorithm [30] is used as a cost function for the optimization algorithm. In the next stage, based on the optimal bands selected, the Local ACE is applied on the image to obtain detection result. Afterwards by applying an appropriate threshold on the detection result, a detection map is produced where the pixels with values above (or equal to) the threshold are assigned to the targets.

However, the main contributions of this study consist of: i) selecting optimal bands based on the target spectrum implantation, ii) improving the conventional target implantation method by applying noise to the images, iii) development of the GWO for band selection in STD domain, iv) defining a new cost function for optimization algorithms used for selecting optimal bands, v) improvement of the method proposed in [28] for determining the appropriate number of bands. vi) generating an appropriate detection map by setting a new detection threshold value for separating targets pixels from the background in the detection result.

The rest of this manuscript is organized as follows. Section 2 describes the materials and methods used including the proposed method and local ACE in details, optimization methods, and datasets. In section 3 experimental results with discussion are given. Finally, section 4 gives the conclusions obtained.

2. Materials and Methods

2.1. Background method

2.1.1. Local ACE Algorithm: ACE algorithm, one of the most useful and common algorithms for detection of sub-pixel and full pixel targets [11, 30, 32], Local ACE is commonly used to detect sub-pixel targets in hyperspectral images [30]. Based on (6), in this version of the ACE algorithm, instead of using the mean and covariance of the entire image, those of just the neighbouring window pixels are used [30].

\[ T_{LocalACE}(x) = \text{sign}((t - m_l)\Sigma_l^{-1}(x - m_l)) \frac{((t - m_l)\Sigma_l^{-1}(x - m_l))^T\Sigma_l^{-1}(x - m_l)}{((t - m_l)\Sigma_l^{-1}(x - m_l))^T\Sigma_l^{-1}(x - m_l)} \]

(6)

where, if \( x > 0 \), then \( \text{sign}(x) = 1 \) and if \( x < 0 \), then \( \text{sign}(x) = -1 \). Also, \( m_l \), \( \Sigma_l \), and \( N \) denote the local average, local covariance, and the number of neighboring pixels, respectively.

2.1.2. GWO algorithm: The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature [36]. Four types of grey wolves such as \( \alpha \), \( \beta \), \( \delta \), and \( \omega \) are employed for simulating the leadership hierarchy [36]. However, a binary version of the GWO algorithm [29] is used in this study to deal with the band selection as binary optimization problems. If each optimizer agent is indicated with \( X \), components of this vector will be 0 and 1, where 1 and 0 stand for selection and unselecting of that bands, respectively. Let us consider the fittest solution as \( \alpha \). Consequently, the second and third best solutions are named \( \beta \) and \( \delta \), respectively. The rest of the candidate solutions are assumed to be \( \omega \).

In order to mathematically model encircling behavior the following equations are proposed [36]:

\[ \underline{D} = |\bar{C} - X_p(t) - \bar{X}(t)| \]

(8)

\[ \bar{X}(t + 1) = \bar{X}_p(t) - \bar{A} \bar{D} \]

where, \( t \) is the current iteration, \( X \) is the position vector of a wolf, \( A \) and \( C \) are coefficient vectors given by:

\[ \bar{A} = 2\bar{a}_1\bar{r}_1 - \bar{a} \]

(9)

\[ \bar{C} = 2\bar{r}_2 \]

where, \( r_1 \) and \( r_2 \) are random vectors in [0,1] and linearly varies from 2 to 0.

2.1.3. PSO algorithm: In PSO for an image with K bands, each particle will be a Kx1-sized vector. In different iterations, each particle's position is updated through the following equation [37]:

\[ X_{id} = X_{id} + V_{id} \]

(10)

where, \( V_{id} \) is the speed of each particle moves inside the search space with a certain speed, while comparing the position of the best solution it has experienced by itself \( (P_{id}) \) with that of all other particles \( (P_{jd}) \). By moving along the path of these two solutions, the particle searches for space, trying to find the best global solution. Thus, \( V_{id} \) is calculated using the following equation [37]:

\[ V_{id} = \omega \times V_{id} + c_1 \times r_1 \times (P_{id} - X_{id}) + c_2 \times r_2 \times (P_{gd} - X_{id}) \]

(11)

where, \( c_1 \) and \( c_2 \) determine the amount of particle's movement towards a local solution as well as a global one. Both \( r_1 \) and \( r_2 \) are random rates between zero and one. Parameter \( \omega \) determines the inertia of the particle’s speed.

2.1.4. MSR and CC PSO-based Methods: The MSR and CC are two cost functions in PSO-based band selection methods [5]. I MSR aims to selecting those bands in form of (12) are selected.

\[ \text{argmax} \sum_{i=1}^{M} \frac{M}{SM(\theta^i)} \]

In (12), \( M \) is pixel average with the highest amount of ACE along with its four adjacent pixels and SM is an
average of 10 pixels with highest amount of ACE, except for the five ones in \( M \). Also, \( \varphi^2 \) is a set of selected bands.

In CC method, the correlation between the outputs is measured by means of all bands as well as the selected ones and the sum of bands, maximizing this correlation is introduced as the selected bands. If we term ACE output for the use of both all bands and the selected ones along with their averages as \( O_1, O_2, O_3, \) and \( O_4 \), for an \( m \)×\( n \) image, the cost function of CC is defined as below.

\[
cc = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} (O_{1ij} - O_{2ij}) (O_{2ij} - O_{4ij})}{\sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} (O_{1ij} - O_{4ij})^2 (\sum_{i=1}^{m} \sum_{j=1}^{n} (O_{2ij} - O_{4ij})^2)}^2}
\]  

(13)

2.2. Proposed method

Fig. 1 shows flowchart of the proposed method for STD in hyperspectral images.

As can be seen in Fig. 1, the first step of the proposed method is to implant synthetic targets in the image. The desired target spectrum is implanted in some image pixels randomly as training and test data. Since in the field of target detection, the frequency of the target presence in the images is basically scarce, the number of host pixels for implantation has been determined with a very small percentage of all image pixels. In this study, the synthetic targets are created via the conventional target spectrum implantation method [23] as follows:

\[
z = f \cdot t + (1-f) \cdot b \tag{1}
\]

where, \( f \) is the fraction of target spectrum implantation, \( t \) is target spectrum, and \( b \) is selected pixel spectrum for implantation that results in the generation of the simulated target \( z \). The amount of \( f \) is determined based on the size of both image pixel and the targets. In (1) the target spectrum in all bands is added to the host pixels with a constant proportion, whereas due to the presence of noise, imaging circumstances and the impacts of adjacent pixels in reality this will not be so. Accordingly, using the method presented in [31], based on a predefined signal-to-noise ratio (SNR), this study suggests applying some noise to the reflection image. The generated noise contains spectral correlation, in which the components of the covariance matrix, being a Toeplitz Matrix, are obtained for each two arbitrary bands \( i \) and \( j \), as follows:

\[
C_{ij} = \frac{\delta[X^T X]}{\text{SNR}_{ij}} \cdot \delta^{(i-j)} \tag{2}
\]

where, \( X \) is a two-dimensional matrix, composed of \( L \)-dimensional vectors of all image pixels, while, \( \delta \) and \( \text{SNR} \) are the controlling parameters of spectral correlation and the SNR in dB, respectively.

Once the synthetic targets are created, the optimal bands are selected via an optimization algorithm such as PSO in both internal and external rings, wherein the internal ring selects the optimal bands while the external one determines the number of them. Unlike the method presented in [28], the cost function and the coefficients, defined for inner and outer optimization algorithm vary in this research.

One of the methods for determining the accuracy of target detection algorithms is a false alarm (FA) index. The lower the FA, the greater the accuracy of that algorithm. As it falls, ACE rate becomes maximum in the target pixel’s position (number 1). Therefore, the cost function for inner optimization is defined based on (3), as mean ACE (mACE), enabling optimization algorithm to maximize ACE at the training implanted target by means of the selected bands (\( \Omega \)). Eventually, those bands are selected which maximize average ACE at the implanted targets.

\[
mACEcost_A = \arg \{ \max_A (mACE_{train}) \} \tag{3}
\]

Hence, for the outer optimization, based on (4), minimization of FA (mFA) is introduced as the cost function for establishing detection reliability of 95% from implanted test targets.

\[
mFAscot_A = \arg \{ \min_A (FA_{test}) \} \tag{4}
\]

In the final stage, the Local ACE algorithm using the optimal bands selected is conducted on the main image. The output is a detection result, which requires applying a detection threshold value for separating targets from the
background pixels. The detection threshold value (τ) is usually estimated using a Constant False Alarm Rate (CFAR) processor [32] or the following equation [33]:

$$
\tau = \mu_d + z_\alpha \sigma_d
$$

(5)

where, $\mu_d$ and $\sigma_d$ are the mean and standard deviation of the detection result and $z_\alpha$ is the z statistic at a significant level of $\alpha$, which controls the number of pixels declared as target. However, in this study, the threshold value (τ) is estimated by calculating the minimum ACE value among the implanted target pixels in the detection result. Obviously, this method requires no prior information and thus is free from any input parameter setting.

2.3. Datasets

2.3.1. HyMap dataset: This dataset, also called Target Detection Blind Test [34], includes reflection and radiance image of Cook City, State of Montana, United States (see Fig. 2). The HyMap hyperspectral image includes 126 spectral bands with 2808800 pixels with a 3-meter spatial resolution with 12 targets in different sizes. Table 1 presents the type and dimensions of the targets.

Table 1. Characteristics of the targets in HyMap dataset

<table>
<thead>
<tr>
<th>Name</th>
<th>Size(m²)</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>3×3</td>
<td>Red Cotton</td>
</tr>
<tr>
<td>F2</td>
<td>3×3</td>
<td>Yellow Nylon</td>
</tr>
<tr>
<td>F3a</td>
<td>2×2</td>
<td>Blue Cotton</td>
</tr>
<tr>
<td>F3b</td>
<td>1×1</td>
<td>Blue Cotton</td>
</tr>
<tr>
<td>F4a</td>
<td>2×2</td>
<td>Red Nylon</td>
</tr>
<tr>
<td>F4b</td>
<td>1×1</td>
<td>Red Nylon</td>
</tr>
</tbody>
</table>

2.3.2. Hyperion Dataset: The Botswana dataset was acquired by the Hyperion sensor at 30m pixel resolution over a 7.7 km strip in 242 bands covering the 400-2500 nm portion of the spectrum in 10nm windows (see Fig. 2). The UT Center for Space Research performed pre-processing of the data. Uncalibrated and noisy bands were removed, and the remaining 145 bands The data analysed in this study, acquired May 31, 2001[35]. The exposed soil with 56 pixels has selected as a searched target.

3. Experimental Results

In this study, selecting optimal bands for STD using GA, GWO and PSO optimization methods based on MSR, CC and mACE cost function are compared. Basically, in spectral bands selection procedures, such criteria as increasing detection accuracy, data size reduction, computational complexity, and processing time reduction are given account. The proposed method is used to reduce data dimension and increase the accuracy of target detection. In order to compare the detection efficiency of the proposed method, the FAR measure has been adapted. FAR is the ratio of the number of pixels, falsely detected as target, to total pixels of the image.

3.1. Pre-processing

3.1.1. Implant fraction: Implant fraction should be specified based on the size of target of interest as well as the spatial resolution of the image. Given the area of each image pixel (9 m² and 30 m² for Hymap and Hyperion datasets, respectively), the spectrum of the target of interest is implanted with a fraction of (target area/ pixel area) in a randomly set of host pixels of the image. The number of host pixels for implantation is considered to be 0.05% of the number of pixels of the image.

3.1.2. SNR setting: In order to add noise to the original image, based on (2), spectral correlation and SNR have been considered to be 0.8 and 30, respectively.

3.1.3. Optimization algorithms set up: In this study, the optimization algorithms are implemented in maximum 1000 cycles with initial agent (particle, population, and wolf) sizes of 200, 200, and 12 for PSO, GA, and GWO algorithms, respectively. Optimization algorithm has two terminate conditions, namely 400 cycles without any improvement in the optimal best solution or reaching the optimal best solution of -1. It is necessary that in the outer optimization algorithm the number of bands should drop...
respectively. Due to the band’s correlation in hyperspectral images and excessive processing time, the number of bands declined by five in each cycle of the outer optimization ring.

The speed rate and movement inertia of the agent’s for PSO algorithm has been 1, with coefficients $c_1$ and $c_2$ being 1 and 2, respectively. In GA, the possibility of mutation and crossover are 0.2 and 0.8, respectively. The generation being equal to 1000.

3.1.4. Local ACE set up: In local ACE algorithm, the dimensions of internal and external windows were considered with kernel size $3 \times 3$ and $5 \times 5$ so that the range of target pixel as well as background pixels could be determined, considering the target dimensions and spatial resolution of the image.

3.1.5. CC and MSR set up: Given the presented results in [5], the rate of $K$ for cost function of MSR was considered 10. Since these cost functions are quite time consuming, two regions are with sizes of $300 \times 100$ and $300 \times 128$ are cropped from Hymap and Hyperion images, respectively (see Fig. 3).

![Cropedregions.png](https://via.placeholder.com/150)

**Fig. 3.** The cropped regions of Hyperion (a) and Hymap (b) images.

3.2. Performance Evaluation of the Proposed Method

After the pre-processing stage, the optimization algorithm is implemented to count the bands and select the optimal one. Once the optimization algorithm is done, the rates resulting from mACE and mFA cost functions in the outer optimization are drawn on the test pixels. Fig. 4, shows convergence diagrams of inner and outer PSO algorithm using mACE and mFA cost functions, respectively, obtained on F4 and the exposed soil, as two sub-pixel targets, in the Hymap and Hyperion images, respectively.

As shown in Fig. 4, by decreasing the number of bands, the rate of mACE value has increased for both training and test samples. Therefore, to increase mACE value in the pixels, this cost function tries to select fewer bands with more ACE output values. However, the small number of bands in detection methods will not bring acceptable results. To solve this problem, unlike [28], the mFA cost function is used for outer optimization and mACE is employed for inner optimization.

![ConvergenceDiagram.png](https://via.placeholder.com/150)

**Fig. 4.** Convergence diagrams of inner and outer PSO algorithm obtained on F4 (a) and the exposed soil (b) in Hymap and Hyperion datasets. The outputs of outer optimization have been normalized between zero and one.

From Fig. 4, the diagrams of the outer optimization algorithm show that by increasing the number of bands, the FAR with a reliability of 95%, is initially decreased and then ascend. Also, at one point, wherein FA equals zero, the number of appropriate bands is determined. As can be observed from Fig. 4, the number of optimal bands is 25 and 10 for the targets F4 and the exposed soil in Hymap and Hyperion datasets, respectively. In addition, the results show that, the number of optimal bands obtained for the targets F3 and F7 in Hymap dataset is 25. Also, 30 optimal bands is...
obtained for the rest of targets in Hymap dataset. Also in the case of the cropped image, 300×100 pixels, apart from target F5, for which 35 bands has been selected, other targets give the same 25 and 30 optimal bands. Fig. 5 illustrates the detection results and maps obtained by the proposed method to detect F4 and the exposed soil, as two sub-pixel targets in the Hymap and Hyperion datasets, respectively.

![Fig. 5. Detection results and detection maps obtained by the proposed method on F4 (a) and the exposed soil (b).](image_url)

Tables 2 and 3 give the FARs for each of the methods in Hymap and Hyperion datasets, respectively. The results on the entire images have been obtained from three times run of the optimization algorithms using mACE and mFA cost functions in inner and outer rings, respectively. Moreover, the comparison of the cost functions on the image subsets has been done using the PSO algorithm, which was also used in [5].

**Table 2. FAR in Hymap scene**

<table>
<thead>
<tr>
<th>Target name</th>
<th>On the entire image (multiplied by 10^5)</th>
<th>On the subset of 300×100 pixels of the image (multiplied by 10^5)</th>
<th>Optimization algorithms</th>
<th>Cost functions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Bands</td>
<td></td>
<td>GA</td>
<td>PSO</td>
</tr>
<tr>
<td>F1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F3a</td>
<td>2.2</td>
<td>2.2</td>
<td>1.7</td>
<td>1.7</td>
</tr>
<tr>
<td>F3b</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F4a</td>
<td>25.4</td>
<td>17.8</td>
<td>6.2</td>
<td>4.0</td>
</tr>
<tr>
<td>F4b</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F5a</td>
<td>5.3</td>
<td>1.7</td>
<td>0.8</td>
<td>0.4</td>
</tr>
<tr>
<td>F5b</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F6a</td>
<td>2.2</td>
<td>1.7</td>
<td>0.8</td>
<td>0</td>
</tr>
<tr>
<td>F6b</td>
<td>0.8</td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>F7a</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>F7b</td>
<td>0.8</td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
</tr>
</tbody>
</table>

**Table 3. FAR in Hyperion scene**

<table>
<thead>
<tr>
<th>Target Pixel No</th>
<th>On the entire image (multiplied by 10^2)</th>
<th>On the subset of 300×128 pixels of the image (multiplied by 10^2)</th>
<th>Optimization algorithms</th>
<th>Cost functions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Band</td>
<td></td>
<td>PSO</td>
<td>GA</td>
</tr>
<tr>
<td>P1</td>
<td>29.4</td>
<td>24.6</td>
<td>2.8</td>
<td>2.8</td>
</tr>
<tr>
<td>P2</td>
<td>3</td>
<td>1.4</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>P3</td>
<td>72</td>
<td>26.3</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>P4</td>
<td>56.5</td>
<td>53.9</td>
<td>13.1</td>
<td>13.1</td>
</tr>
<tr>
<td>P5</td>
<td>8.4</td>
<td>11.4</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>P6</td>
<td>92.3</td>
<td>68.3</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>P7</td>
<td>100</td>
<td>100</td>
<td>77.7</td>
<td>77.7</td>
</tr>
<tr>
<td>P8</td>
<td>90.4</td>
<td>45.8</td>
<td>2.4</td>
<td>2.4</td>
</tr>
<tr>
<td>P9</td>
<td>98.2</td>
<td>84.3</td>
<td>46.9</td>
<td>46.9</td>
</tr>
<tr>
<td>P10</td>
<td>86.3</td>
<td>70.9</td>
<td>12.4</td>
<td>12.4</td>
</tr>
<tr>
<td>P11</td>
<td>3.9</td>
<td>0.6</td>
<td>0.006</td>
<td>0.006</td>
</tr>
<tr>
<td>P12</td>
<td>2</td>
<td>0.3</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>P13</td>
<td>1.5</td>
<td>0.8</td>
<td>0.7</td>
<td>0.7</td>
</tr>
</tbody>
</table>
Tables 2 and 3 clearly show the predominance of the presented method over the compared ones. In addition to the FAR, the number of selected bands should be considered. As an example, on the target F7b that has 25 selected bands with respect to the full band, despite the significant decrease in the number of bands, FAR was still recorded to be zero. Also, from the tables 2 and 3, it can be seen that GWO achieves the best solution, which confirms that it can perform better than PSO and GA for STD tasks. As the results show, the proposed method is able to increase the accuracy of detection procedure, despite large reduction of data size in all cases. According to Table 2, FAR has not become zero for some targets. As can be seen in Fig. 6, the ACE output values in some other pixels are high. This is due to the presence of the target spectrum in these pixels. In fact, because of the point spread function effect these pixels. In fact, because of the point spread function, the target spectrum with larger dimensions (available in Table 1) is broadcast in a few pixels and causes such an agreement.

![Fig. 6. Outputs of ACE algorithm for target pixels and their neighbours (in vicinity of 100 pixels).](image)

To compare the robustness and repeatability of of the optimization algorithms, Table 4 and Fig. 7, show statistical parameters values obtained from 20 runs of the optimization algorithms on the datasets.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>PSO</th>
<th>GA</th>
<th>GWO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hymap</td>
<td>0.0123</td>
<td>0.0125</td>
<td>0.00118</td>
</tr>
<tr>
<td>Hyperion</td>
<td>0.03991</td>
<td>0.03898</td>
<td>0.02769</td>
</tr>
</tbody>
</table>

From Table 4, GWO provides the minimum standard deviation value, which proves their stability, repeatability, and ability to reach optimal regardless of the used randomness and initial positions of the search agents. Also, from Fig. 7, GWO in both datasets offers statistical better searching capability compared to the PSO and GA.

3.3. Discussions

3.3.1. Noisy band removal: In this study, noisy band removal was not necessary for two reasons: First, despite the low information, each of the image bands can be an influential band in target-background spectral separation and second, in the proposed method, damaging and unusable noise bands are automatically removed from the image due to not assisting spectral separation of the target from the image background.

3.3.2. The processing time: In addition to FAR, the processing time parameter is influential and decisive too, when determining the quality of band selection methods. Since in cost functions of MSR and CC, at each stage of optimization cycle, it is necessary to apply detection algorithm on the entire image once, this process will be quite time-consuming. On the contrary, in the presented algorithm, the detection algorithm was applied only on 100 simulated pixels in each cycle. As for MSR and CC with image sizes of 100*300 and 128*300 pixels, respectively, 4 to 5 hours are spent on band selection, whereas in case of mACE Cost, this period got dwindled less than 1 minute on average for all three optimization methods. In addition, the PSO, GA and GWO optimization algorithms spent an average of 200, 120, and 400 seconds to achieve the best solution for detecting different targets.

![Fig. 7. The statistical parameters of fitness values obtained from 20 runs of the optimization algorithms on Hymap (a) and Hyperion (b) datasets.](image)
The results demonstrate that GWO reached the best solution with a smaller number of iteration. However, increasing the number of wolves from 12 to 200 increases the processing time by eight times. Moreover, the PSO algorithm converges with less speed than GA and GWO methods. It should be noted that, PSO does not involve any mutation operator. This may be the main reason of superiority of PSO to its counterparts.

### 3.3.3. The cost functions: According to (13), one of the most important problems of CC cost function is that it innately tends to increase the data size and select more bands. Thus, CC reaches the maximum rate (number 1) when nominator and denominator of the fraction are equal to one another, occurring when the number of selected bands is equal to the number of original image's bands, i.e. 126. Therefore, this algorithm tends to increase the number of bands. However, considering (3), cost function of mACE innately tends to reduce the data size and select fewer bands, because for a set of N members, the components of which are between 0 and +1, the average of M out of N members inclines towards maximizing when M has one member and that member is the maximum amount of the N-member group. As a result, this algorithm inclines towards decreasing the number of members or bands.

### 3.3.4. Superiority of PSO to GA: Comparing GA algorithm with PSO algorithm, two points are important. The first point is the connection and information transfer among the particles in PSO algorithm and second the ability to save the experiences for each particle. These features allow the PSO algorithm to arrive the best solution faster. Note that, GA because of crossover or mutation, all or part of the agent changes, cannot use previous information completely.

### 3.3.5. Sensitivity of the outer optimization algorithm to the presence of noise: In target implantation, the amount of noise applied to the image has an important role in reaching the optimal answer. This can be observed in Fig. 9 which shows FA values obtained on Hymap dataset using PSO optimization algorithm in several SNR value ranges from 1 to 50 dB. From this figure, if the added noise value is too small, the SNR will be increased, and consequently, the local ACE detector easily detects implanted pixels. Therefore, FAR value for outer optimization algorithm is almost constant and approximately equal to implanted test pixels' number (see Fig. 9.a).

On the other hand, if the amount of added noise is too high, the probability of detecting implanted test pixels will be very low and FAR values do not follow a specific pattern (see Fig 9.f). In what follows, it is necessary to apply some noise after target spectrum implantation to the image. According to the results obtained, the suitable amount of SNR was determined 30 dB.

### 3.3.6. Detection threshold: In this study, the new threshold estimation method is compared to the two conventional methods [32, 33] based on the overall accuracy measure. The higher overall accuracy shows the more precise in target and background pixels' identification. Inspired by [38], \( z_{\alpha} \) in Equation (5) is regarded to be 3. and CFAR which introduced in [32], was set to 0.001, inspired by [39]. Table 5 shows the performance comparison of the proposed threshold estimation method and the two conventional methods on the fabric targets and the exposed soil in Hymap and Hyperion datasets, respectively, using the overall accuracy statistic.

---

**Fig. 8.** Convergence curve of the PSO algorithm using different cost functions (a) and the optimization methods (b). The x-axis shows the number of iteration of the loop and the y-axis shows the best solution in each iteration.

**Fig. 9.** FA values obtained on Hymap dataset using PSO optimization algorithm in several SNR values.
4. Conclusions

This study presented a new band selection method for STD in hyperspectral images based on implanting synthetic targets and using optimization algorithms with two new cost functions, mACCEcost and mFACcost, in Local ACE target detection algorithm. In this study, GA, binary GWO, and PSO optimization algorithms were investigated. Moreover, a new threshold estimation method was also proposed using the minimum ACE value among the implanted target pixels in the detection result.

The performance of the proposed method was evaluated in this study on Hymap and Hyperion hyperspectral datasets. The obtained results find out that the binary GWO algorithm and mACE cost function outperforms other methods in the search capability and feature selection, respectively. In addition to reducing data size, complexity, and computational time, the proposed method was able to increase the accuracy of detection. Furthermore, the detection threshold estimation method has increased overall accuracy over the two commonly used methods.

The key point in reaching the best solution, in addition to an appropriate determination of optimization coefficients, is to have information on the target spectrum as well as its dimensions. Obviously, the more similar of the implanted pixels and their adjacent pixels to the real space of the target in the image, the better the results, released by the optimization algorithm used. Additionally, when determining optimization coefficients, including the number of agents and the maximum number of iterations, considering the computation time, one can reach more reliable solutions by spending more time.

In order to develop the proposed method, in more complicated images, via image clustering, one can implant a certain number of target spectra in each cluster, depending on the cluster and image size, then to select the optimal bands for each cluster and detect the targets in that cluster. Furthermore, to increase target simulation quality, one can use the formula presented in [22] for target implantation. In this equation, during implantation, the influences of the target's presence in the adjacent pixels are also taken into account.

5. Acknowledgment:

The authors would like to thank the digital imaging and remote sensing group centre for imaging science at Rochester Institute of Technology, NY, for providing the HyMap dataset and specially Dr. John P. Kerekes for his valuable help in providing the position of blind-test targets.

6. References


