Target detection based on a dynamic subspace

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ABSTRACT

For hyperspectral target detection, it is usually the case that only part of the targets pixels can be used as target signatures, so can we use them to construct the most proper background subspace for detecting all the probable targets? In this paper, a dynamic subspace detection (DSD) method which establishes a multiple detection framework is proposed. In each detection procedure, blocks of pixels are calculated by the random selection and the succeeding detection performance distribution analysis. Manifold analysis is further used to eliminate the probable anomalous pixels and purify the subspace datasets, and the remaining pixels construct the subspace for each detection procedure. The final detection results are then enhanced by the fusion of target occurrence frequencies in all the detection procedures. Experiments with both synthetic and real hyperspectral images (HSI) evaluate the validation of our proposed DSD method by using several different state-of-the-art methods as the basic detectors. With several other single detectors and multiple detection methods as comparable methods, improved receiver operating characteristic curves and better separability between targets and backgrounds by the DSD methods are illustrated. The DSD methods also perform well with the covariance-based detectors, showing their efficiency in selecting covariance information for detection.

1. Introduction

Targets in the remote sensing domain refer to ground objects of special interest [1–3]. For example, vehicles on a road comprise the targets when the extraction of their accurate positions is the main task. The spectral differences between target and non-target backgrounds is the foremost feature in target detection by hyperspectral remote sensing imagery, which makes it a two-class classification problem. However, targets in remote sensing images usually occupy only a small fraction of the whole image, with each having a limited size. As a result, the minimization strategy for the misclassification error cannot be used in target detection, otherwise all the targets would be labeled as background [2,3].

Remote sensing target detection methods contrarily focus on maximizing the probability of detection with a certain constant false alarm rate, which originates from the signal estimation and detection theory in the communications field [4–6]. Thus, the target pixel is considered as the signal of interest to be detected. In this way, the problem is transformed into a signal processing procedure. This is the main idea behind the signal detection based methods, including the finite impulse response filter, likelihood ratio test, hypothesis testing, and so on [1,2,7–9]. Other methods exploit the linear spectral mixture [10,11], assuming that each pixel consists of different endmembers. “Endmember” refers to a pure pixel of the land object in the image and presents a unique spectral feature. The difference between different endmembers is the key to interpreting hyperspectral images. This approach is widely used in spectral unmixing from hyperspectral images [12, 13]. However, the distinction is that unmixing decomposes the scene into all the constituent materials in their proportions, whereas target detection should give a more or less binary indication of the presence of a single material or class of interest.

In spite of their different theoretic origins, many detectors can be considered as subspace-based detectors as the information about targets and backgrounds is reserved in the subspace. Two important ways of constructing subspaces shall now be considered. One way is to use the different endmembers’ spectra as a basis to compose the target subspace and background subspace, respectively. In other words, the composite units in the spectral mixture model are used. The other approach is to selectively choose bands from the image as a subset to make up the subspace, which is actually a band selection procedure. However, both approaches have the following drawbacks. They both use the same subspace background construction method for different imagery; that is, they choose the whole dataset as background. The resulting subspace will cause a drift to the inverse direction of the main direction of the subspace in the feature space [15], or a contaminated background subspace [16–18]. Research has been undertaken to prove that different pixels in
different regions usually contain different backgrounds [19], due to the discontinuous and inhomogeneous nature of real-world landscape composition.

Other researchers have reported that the spectrally similar pixels are actually on the same patch in the whole manifold feature space [20–25], which is another clue as to the local subspace construction. Furthermore, a locally constructed subspace provides an efficient way to avoid the limitation of the data distribution [26–28]. A typical example is the Gaussian distribution assumption, which is the one most widely used in most detection methods, although, in many cases, the assumption is not reasonable [29–31, 33]. In fact, with the local subspace, only the linear relationship between the pixel under observation and the neighborhood pixels is used. Therefore, no assumption about the data distribution is taken into consideration.

Above all, targets pixels usually reside in parts of the feature space, so a rigid global subspace may not be able to model different pixels very well. The corresponding background subspace should be elaborately constructed from certain pixels of the image dataset. The problem then lies in the fact that with only certain of the target pixels for training in the image we can find the most suitable background subspace for the exact and robust detection of the rest of the target pixels. Several studies have been undertaken on dynamic subspace construction for a classification problem [34–36]. After dynamic subspace formulation, a fusion strategy is usually undertaken. Some work on the fusion method for hyperspectral target detection has already been undertaken [37–40].

In this paper, we take a dynamic selection strategy as the method for constructing the subspace. However, since the spectral resolution is one of the main advantages for hyperspectral images to be able to differentiate a target of interest from the spectrally similar background objects, the subspace construction manner in previous papers, which choose a subset of bands from the complete set of bands, known as band selection, is not used. In contrast, the subspace is not selected randomly from the different bands, but constructed by the randomly selected pixels. Iterative procedures are then carried out to evaluate the performance of the dynamic subspaces to detect the training target pixels and, finally, to obtain the most suitable one for each detection procedure. The criterion is to determine the proper number of pixel blocks for the subspace construction for the detector in each detection procedure. We then choose from the image dataset those pixel blocks under this number that present the optimal detection performance for each detection procedure. Furthermore, the manifold patch structure is also taken into consideration in optimizing the subspaces by eliminating the anomalous pixels on the manifold feature space. Then, with the remaining pixels, multiple detection procedures based on the corresponding subspaces are undertaken independently, and fused afterwards to obtain a robust detection result. Our contributions in this manuscript can be summarized as:

1. Given limited training target pixels, our method tries to find the most suitable pixels to construct the subspace for the detection, so as to have enough discriminative ability to separate the individual targets.
2. With two nested performance analysis procedures, our method is able to choose the most informative pixels for the construction of the detector in a certain detection procedure.
3. By constructing a multiple-detector strategy, our method is believed to be robust with regard to the complex backgrounds in the image scene. Despite the possible contamination of targets in the formulation of the particular detection procedure, target pixels can still be determined by a final fusion of all the detection procedures.
4. The proposed dynamic subspace detection (DSD) theory is applicable to a covariance-based detector. It is also a useful background statistics estimation and selection criteria, and it provides a standard framework for optimized detection methods employing any basic state-of-the-art detector.

The remainder of this paper is organized as follows. Section 2 formulates the proposed DSD framework. Section 3 describes the experiments used to test our proposed method and presents the results of these experiments in comparison with other state-of-the-art detection methods. Finally, Section 4 summarizes the paper.

2. The dynamic subspace detection (DSD) method

In this paper, the background pixels’ dataset is computed from the whole dataset. The choosing criterion is to ensure that the corresponding subspace can better augment the separability between target and non-target pixels in the detection procedure. Separability is the key to judging the performance of target detectors. It refers to the ability to separate a target of interest from the background by a certain detection method. It can be measured by the statistics of the target and background values after detection. A promising method should be able to suppress the background into a comparably low-value range and extrude the target pixels into a high-value range. The majority of the target pixels’ values and the majority of the background pixels’ values are expected to be distributed in a diverse range, or a gap between them is preferred. The target subspace is fixed as the number of target pixels is so low. Therefore, the manufacture of the background subspace is the key step. The following estimations are done on a whole single hyperspectral image. With the training target pixels, we want to choose the most suitable background pixels for constructing the background subspace.

2.1. Determination of the blocks for each subspace construction

Due to the rarity of the target pixels, the target subspace is actually made up of the mean spectra of the target training samples, or the signatures from the spectral library. Meanwhile, the background subspace is dynamically chosen from the whole dataset. In the dynamic subspace classifiers, the number of bands used to construct each subspace has to be determined [36], whereas in our method, the number of pixels chosen to construct the background subspace should be determined.

Unlike dynamic subspace classification (DSC) [35,36], which chooses bands from raw high-dimension samples by randomly projecting them into a subspace where all the samples have a zero constant in the unselected dimension, a method of assembly is used in our method. A subset of pixels is randomly selected from the whole dataset and assembled to form a subspace for a certain detector, such as the adaptive matched subspace detector (AMSD), adaptive cosine estimator (ACE), and so on [23]. This procedure is based on the assumption that a subset, instead of the whole dataset, may be more appropriate and reasonable for a linear subspace [33], which is consistent with the “locally linear, globally non-linear” assumption in manifold learning methods [20,41–45].

In order to obtain typical background pixels for the subspace construction, and to increase the probability of hitting pure pixels, a block structure is used as the basic choosing unit, instead of a single pixel. The whole image is segmented into many blocks, and a block is defined as a square with a size of \( \text{floor}(\sqrt{L+1}) \times \text{floor}(\sqrt{L+1}) \), where \( L \) is the band number, and \( \text{floor()} \) refers to the integral function. Each pixel corresponds to a certain block and lies in the center of the block, so the blocks are overlapping. The purpose is to ensure that the detector is composed of the more representative pixels. The number of blocks is determined by an evaluation of the importance of the block datasets with different numbers of blocks. A vector probability mass function, termed \( \mathbf{Cd} \).
is drawn from their detection performance; it is characterized as the detection performance. \textbf{Cd} shows the importance of the different block datasets, which is used as the evaluation of modeling the probability of block numbers to be selected. This procedure is described in detail in Section 2.1. Furthermore, another distribution to find which blocks are preferred is also computed, given a fixed number of blocks, then an iterative procedure with both \textbf{Cd} and the distribution is undertaken until all the detection procedures are computed.

Suppose that a fixed number (\(P\)) of blocks need to be selected. Firstly, we should construct the detection performance analysis of different single blocks from the imagery dataset. Since the number of pixels should be no less than the number of bands, the basic size of the block should be enlarged. A benchmark detection method is chosen as the basic detector to apply to the different blocks. Thus, each block will have a performance record, and the according detection probability is computed. The equation is expressed as follows:

\[
F_{AM}(i) = \frac{q(i)}{\sum_{i} q(i)}
\] (1)

where \(q(i)\) is the detection probability rate for the \(i\)th block (\(i = 1, ..., N_p\), \(N_p\) is the total number of blocks of the image). For a certain block, it is used to construct a detector, such as AMSD or ACE [23]. An average of the target training pixels is used as the target spectrum in the detector to obtain the detection results. The reference spectrum in the detector to obtain the detection results. The reference dataset, and \(A\) is randomly generated on \(r\) which chooses the suitable blocks when the number of blocks is determined. The above composition of blocks is not necessary. In fact, different levels of block numbers are used to compose this group.

In detail, with each selected block of pixels, the statistics for the basic detectors’ formulation can be computed. Taking AMSD as an example, its covariance is calculated as

\[
\bar{T}_b = \frac{1}{N_x} \sum_{j=1}^{N_x} x(j) x(j)^T
\] (2)

where \(x(j)\) is the training pixels from the chosen blocks, and \(N_x\) is the number of pixels in each block.

The number of pixels representing the targets per \(i\)th block at a fixed false alarm rate of \(10^{-4}\) is then a random variable with the probability mass function (pmf) \textbf{Cd}: \(f_{AM} = f_{AM}(1), f_{AM}(2), ..., f_{AM}(N_p)\).

Based on the above probability mass function \textbf{Cd}, a procedure similar to pseudorandom number generation is constructed to select the predefined \(P\) blocks. An iterative procedure is proposed here. Each cycle chooses a certain block, and the steps are as follows:

Step 1: A uniform number \(r\) is randomly produced on [0, 1]. This value range is to confirm that the percentage can be used as a detection probability.

Step 2: Calculate the cumulative distribution function \(F_{AC}(i)\) of \(f_{AM}(i)\). This can be done by simply summing up the cut-off accumulation until \(f_{AM}(i)\):

\[
F_{AC}(i) = \frac{\sum_{j=1}^{i} f_{AM}(j)}{\sum_{j=1}^{N_p} f_{AM}(j)}
\] (3)

Step 3: Choose the \(L\)th block if the following equation is met:

\[
F_{AC}(L-1) < r < F_{AC}(L)
\] (4)

which means that the block presents the proper detection according to \(r\).

Step 4: Let \(f_{AM}(L) = 0\), and update the \(f_{AM}\) in \textbf{Cd} and the corresponding cumulative density function \(F_{AC}(i)\).

Each cycle (Steps 1–4) is performed \(P\) times so as to get the predefined \(P\) blocks. The procedure is defined as \(B_k = \text{DSC}_1(B, P, F_{AC})\), where \(B\) refers to the whole imagery pixels’ dataset, and \(B_k\) represents the \(P\) blocks of pixels chosen from \(B\) by means of the \(F_{AC}\) distribution. In other words, based on the performance of each block, and the pseudorandom procedure, when a fixed number \(P\) is given, \(P\) blocks can be obtained. The number \(P\) then has to be determined. The above iteration is called Selection Procedure I.

2.2. Determination of the number of blocks to construct the subspace

A single detector can be constructed with different numbers of blocks. We can therefore analyze the different performances and determine the appropriate number of blocks. Another pseudorandom number generation procedure is employed to determine the appropriate number of blocks to construct the subspace. However, one difficulty here is that the candidate number should not be too large, in order to alleviate the computational burden in Selection Procedure I, and it is also limited by the image size.

We can use a predefined block number to select the different pixels, and these pixels constitute an “element”. We perform this procedure several times, and all the elements constitute the “subsets of pixels”, where each element corresponds to a number of blocks. In detail, the optimal number of blocks is supposed to be based on a continuous distribution \(Bn\). Subsets of pixels with different numbers of blocks are evaluated in the target detection, and the detection performance is recorded. The corresponding discrete members are computed for \(Bn\). A density estimation method is then used to smooth the discrete detection records into a continuous distribution. With this distribution, a pseudorandom-based method is again used to decide the optimal size of the subspace dimension. The above procedure is also done by iteration and can be implemented as the following steps:

Step 1: A number \(r\) is randomly produced on [0, 1].

Step 2: Produce a group \((G)\) of representative subsets, where each subset has a different number of blocks, determined by \(b_{n1}, (i = 1)\)

\[
b_{n1} = (i-1) \times \frac{N_x}{N_p}, \quad (i = 2, ..., N_p)
\] (5)

where \(i = 1, ..., N_p\), \(N_p\) is the number of representative block subsets, which is predefined subjectively, with a larger number requiring a higher computational burden. The number range for \(N_p\) is between 34 and 40. Although a number greater than 40 presents a better performance, the improvement is very small. \(N_p\) is the total number of blocks in the image. It is assumed that obtaining a subset covering every possible composition of blocks is not necessary. In fact, different levels of block numbers are used to compose this group.

Step 3: For each subset \(b_{n1}\) in the group, determine its composition \(B_{n1} = \text{DSC}_1(B, P, F_{AC})\) by Selection Procedure I, which chooses the suitable blocks when the number of blocks has been given.

Step 4: Based on the detection performance of the different subsets \(B_{n1}\), the performance is evaluated as

\[
f_{AM}(i) = \frac{DB_{n1}(i)}{TN}
\] (6)

where \(DB_{n1}(i)\) is the number of detected pixels by the subset \(B_{n1}\) and \(TN\) is the total number of training target pixels in the image.
A kernel smoothing method is then undertaken to get a continuous distribution \(Bn\) [36,46],
\[
 f_{Bn}(l) = \frac{1}{\sum_{i=1}^{N_b} f_{AM}(t)} \frac{N_b}{\sum_{i=1}^{N_b} f_{AM}(t)k \left( \frac{l-b_{ni}}{\sigma} \right)} 
\]
where \(l = 1, ..., N_b\), and \(N_b\) is the total number of blocks in the whole dataset.

Calculate the accumulative density function \(F_{AC}(i)\) of \(f_{Bn}(l)\):
\[
 F_{AC}(i)^{bn} = \sum_{j=1}^{i} f_{Bn}(l) 
\]

The kernel function \(K\) used in the \(Bn\) distribution is defined as the Gaussian function [36,46]:
\[
 K(l) = \frac{1}{\sqrt{2\pi} \sigma} e^{-l^2/2\sigma^2} 
\]
where \(\sigma\) controls the flattening of the distribution. With a smaller \(\sigma\), the distribution is more salient and the possibility of selecting probabilities of different subsets is also increased. According to [36,46], \(\sigma\) is the bandwidth and is defined as
\[
 \sigma = 0.9 \text{min}^{-1/5} 
\]
where \(n\) is the cardinality of the dataset \(f_{AM}(l)\), and \(A\) is-min. (standard deviation, interquartile range/1.34) [46].

The \(Bn\) distribution computed from the above, corresponding to \(G\), is renamed as \(Bn0\), as it is the first distribution computed from the representative number of subsets, \(G\)’s, performance. The first number of blocks can then be calculated in the following steps.

Step 5: Based on the distribution \(Bnk\) \((k = 0, ..., N_b - 1, N_b\) is the number of detection procedures), choose \(u\) as the number of blocks \(r_{k+1}\), under the following conditions:
\[
 F_{AC}(u-1)^{bn} < u < F_{AC}(u)^{bn}, \quad u = 2, ..., N_n 
\]

Above all, combining the two iterative procedures produces both how many and which blocks are superior and preferred for the detection procedure. For the multiple detection procedures, \(Bnk\) is updated by the detection performance in the previous detection procedure. In other words, each detection procedure needs an individual combined iterative procedure. The updating method for \(Bnk\) is defined as [36]
\[
 f_{Bn}(l) = \frac{1}{\sum_{i=1}^{N_b} f_{AM}(t) + \sum_{i=1}^{N_b} f_{AM}(t_{r_i})} \sigma \times \sum_{i=1}^{N_b} f_{AM}(t)k \left( \frac{l-b_{ni}}{\sigma} \right) + \sum_{i=1}^{N_b} f_{AM}(t_{r_i})k \left( \frac{l-r_{i}}{\sigma} \right), \quad l = 1, ..., N_b 
\]
where \(f_{AM}(t_{r_i})\) is the detection performance according to \(r_i\), computed by the above Step 3 and Step 4.

2.3. Exclusion of outliers by manifold learning

The above two dynamic pseudorandom-based iterative procedures exploit the internal separability between targets and background by means of an optimal detection subspace construction. A manifold learning method is also applied to further eliminate the outlier pixels in the background subsets. Here, the outliers refer to the improper samples for the subspace construction, which are mainly composed of target pixels and the far-away pixels on the manifold. This is based on the assumption that the representative pixels for the background subspace will be from several main patches [45,47–49]. In other words, the far-away anomalous pixels on the manifold are unlikely to be from these patches. This idea is due to the blocks’ composition, with each block containing hundreds of pixels, which will unavoidably include anomalous samples. Since the block has many key supporting pixels for the background subspace, it is chosen as the subspace candidate dataset. However, some outliers may also lie in the block range. In this case, the subspace will be contaminated. In order to eliminate the effect of the block-based choosing strategy, a manifold reconstruction analysis method is used here.

Step 1: For each vector point \(x_i\) in the original high-dimensional feature space, find its \(k\)-nearest neighbors to formulate the dataset \(H_i\), with \(H_i\) representing its \(k\)-nearest neighbor points. Here, the neighbors refer to those nearby spectrally similar pixels, rather than the spatially close pixels. Although the geodesic distance is more appropriate for measuring the neighboring points, the Euclidean distance is actually used for simplicity.

Step 2: Compute the reconstruction weights of the neighboring points of each vector point, on the condition that the error reconstruction of \(x_i\) is minimized. The \(k\)-nearest neighbor points are used to compute the reconstruction weight, and the construction error is defined as
\[
 e_i = ||x_i - \sum_{k \in N_i} a_{ki}x_k||^2 
\]
where \(\sum_{k \in N_i} a_{ki} = 1\) and \(a_{ki} = 0\) when \(x_k \notin N_i\) (\(N_i\) refers to \(x_i\)’s neighboring pixels) are the two constraints. It therefore turns out to be a constrained minimization problem, subject to the above constraints, which can be solved by a least squares method.

Step 3: To get the most suitable block-wise pixels for the subspace construction, pixels with a high reconstruction error are excluded from the chosen blocks of pixels. These pixels will be the target, noise, and spectral anomaly pixels, which are determined by a percentage reconstruction error of over one-twentieth.

For ease of understanding, both the determination of the initial distribution \(Bn0\) and the whole workflow of the multiple detection procedures are illustrated in the following Fig. 1. With Selection Procedure I in Section 2.1, each block subset \(G(i)\) can be constructed by choosing the suitable blocks under the corresponding block number. Then, with the kernel smoothing, the initial distribution \(Bni\) \((i = 0)\) is constructed. The above procedure is shown in the upper part of Fig. 1. With the updating distribution \(Bni\) and the iterative Selection Procedure II in Section 2.1, the multiple detection procedures can be constructed, as presented in the bottom part in Fig. 2. The pseudocodes of the whole algorithms are also listed below. It is worth noting that after the blocks of pixels are chosen from the two successive iterative procedures, they are reevaluated by manifold structure analysis to further exclude the anomalous pixels from the dataset manifold. The remaining pixels are then used to construct the basic detector and to undertake the detection on the hyperspectral image, obtaining the target occurrence image. After a fixed number of detection procedures have been completed, the fusion strategy determines the final results with enhanced frequencies of occurrence. Two different fusion strategies are studied here. One is “majority voting”, which chooses a pixel's final label as the one having the highest frequency of occurrence among all the parallel detection procedures. The other is “overwhelming labeling”, which labels a pixel as a target on the condition that it reaches a certain predefined quota of detections. The influence of different fusion strategies on the final results is investigated in the experiment section (Section 3).

Pseudocode overview of the presented algorithms

Input:
The training dataset \(B\) containing the labeled target pixels and the hyperspectral image
The test sample set \(D\) containing the hyperspectral image
A basic algorithm (detector) \(\Phi\)
The detection procedure number $ND$

The detection probability rate $\varphi(i)$ corresponding to each block

in $B$

Output:

Final detection results $FD$: $Y \rightarrow c \in \{\text{target, background}\}$

A. Training procedure

Begin

Estimate the $f_{AM}$ distribution.

Estimate the $B_{n0}$ distribution.

for $k = 1, 2, \ldots, ND$

Draw $u$ as the number of blocks $r_k$ from $B_{nk-1}$

$B_i = \text{DSC}_k(B, u, F_{BC})$

Obtain $B'_i$ from $B_i$ with pixels with a high reconstruction error form (13) excluded

Construct detector $\Phi'_i$ from $B'_i$ and $\Phi$

Update the distribution $B_{nk}$ by formula (12).

End

B. Detection and fusion procedure

Apply each detector $\Phi'_i$ to the test dataset $D'$

$F = \arg \max c \in \{\text{target, background}\} \text{card}(k\Phi'_i(D') = c)$,

where $k = 1, 2, \ldots, ND$.

Or label a pixel as a target on the condition that it reaches a predefined quota of detections.

3. Experiments and analysis

3.1. Basic detectors and the comparative methods

For evaluating the universality of the proposed multiple-detector framework, two kinds of classic basic detector are used, and they are described in Table 1. Here “basic detector” refers to the state-of-the-art detection methods in the hyperspectral image processing field, with which our proposed method provides a way of achieving a multiple-detector framework to fuse the corresponding detection results and further improve the detection performance. In Table 1, $x$ refers to the pixel observation; $S$ is the target endmember; $B$ is the background endmember matrix and $E = [SB]$ is the concentrated complete endmember matrix; $\bar{T}_B$ is the background covariance; $P_k$ and $P_k$ are the projection matrices onto the column space of matrix $B$ and $E$, respectively; $n$ is the additive noise; $v$ refers to the additive noise plus background; and $a$ is a factor related to the percentage of the pixel area occupied by the target object.

To evaluate and compare the effect of our proposed method, several other algorithms are also constructed, based on the three basic detectors. Here, all the detection methods can be classified into two groups. One group is the structured detection methods, or the
Table 1
Description of the basic detectors.

<table>
<thead>
<tr>
<th>Basic detector</th>
<th>DSDs name</th>
<th>Background characteristics</th>
<th>Detector description</th>
<th>Detection model</th>
<th>Assumptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMSD</td>
<td>DSDAMSD</td>
<td>Structured background subspace</td>
<td>$T_{AMSD}(x) = \frac{c^{T}x - \lambda}{\delta^{2}}$</td>
<td>$H_0 : x = \beta_{AMSD} + \eta$</td>
<td>$P_{F} = 1 - P_{S}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$H_1 : x = \alpha_{AMSD} + \beta_{AMSD} + \eta$</td>
<td>$P_{F} = 1 - P_{S}$</td>
</tr>
</tbody>
</table>

Table 2
Comparative algorithms in the experiments.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Background model description</th>
<th>Detection procedure composition</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACE</td>
<td>Covariance-based model</td>
<td>Using a single ACE detector</td>
</tr>
<tr>
<td>DSDACE</td>
<td>Covariance-based model</td>
<td>Using dynamic subspace construction and fusion of the different ACE detection results</td>
</tr>
<tr>
<td>mACE</td>
<td>Covariance-based model</td>
<td>Using multiple ACE detectors and fusion of the different ACE detections' results</td>
</tr>
<tr>
<td>vDSDACE</td>
<td>Subspace-based model</td>
<td>Same as DSDAMSD except for the exclusion of manifold learning anomaly detection</td>
</tr>
<tr>
<td>GLRT</td>
<td>Covariance-based model</td>
<td>Using a single GLRT detector</td>
</tr>
<tr>
<td>DSDGLRT</td>
<td>Subspace-based model</td>
<td>Using dynamic subspace construction and fusion of the different AMSD detection results</td>
</tr>
<tr>
<td>mGLRT</td>
<td>Covariance-based model</td>
<td>Using multiple GLRT detectors and fusion of the different GLRT detection results</td>
</tr>
<tr>
<td>vDSDGLRT</td>
<td>Subspace-based model</td>
<td>Same as DSDGLRT except for the exclusion of manifold learning anomaly detection</td>
</tr>
</tbody>
</table>

background subspace based methods, which include the single AMSD, where DSD with AMSD is the basic detector (DSDAMSD). The other method in this group is a multiple AMSDs (mAMSD) method. mAMSD employs the same number of AMSD detectors as that of DSDAMSD, and each AMSD randomly selects certain blocks of background pixels, with the total number of blocks being comparable with that of DSDAMSD. The purpose is to make the comparison experiments more equal by using comparable numbers of background pixels. The other counterpart group of methods depends on the covariance-based background, or the unstructured background method, and includes the single ACE, where DSD with ACE is the basic detector (DSDACE), a multiple ACEs (mACE) method, the generalized likelihood ratio test (GLRT), where DSD with GLRT is the basic detector (DSDGLRT); and a multiple GLRTs (mGLRT) method. mACE and mGLRT use the same composition as mAMSD. These algorithms are selected with the intent of exploring with the subspace-based and covariance-based background detection methods. In the fusion procedure of our proposed method (DSD), a pixel will be judged as a target by the criterion defined in Section 2. Another version of DSD, without the manifold outlier elimination, is also used, termed vDSD, so as to evaluate the performance of introducing the manifold information. In order to make a fair comparison of the algorithms, the conventional multiple-detector methods, mACE, mAMSD, and mGLRT, are also employed with manifold analysis. All the above algorithms are described in Table 2. Furthermore, it is noteworthy that for all the multiple-detector methods, in each single detection procedure, the detection threshold is not subjectively determined individually but with a value segmenting the top 0.2% of the pixels, so that the detection methods are immune to the value scale and are not affected by human interaction. In the subsequent sections, the segmentation value is further investigated to evaluate its influence on the final results.

3.2. Simulated dataset experiments and parameter sensitivity analysis

In this paper, extensive experiments are presented to evaluate our method. Both simulated and real-world hyperspectral images are used. Simulated datasets are used due to their definite information about targets, and are employed for the parameter sensitivity analysis, while real-world datasets ensure the practical effect of our method.

The first dataset is the AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) dataset, covering the Lunar Crater volcanic field in Northern Nye County, NV, downloaded from the NASA website (http://aviris.jpl.nasa.gov/html/data.html). The dataset is named “f970623t01p02_r07_sc03”. The low SNR (signal-to-noise ratio) and water vapor absorption bands were removed, reducing the dimensions of the image cube from 224 to 162 bands. This dataset has been widely used in hyperspectral image processing research [19,50–52]. A two-pixel ore object is considered as the target of interest. The false color picture of the scene is shown in Fig. 2, where an arrow labels the target’s position. However, due to the scarcity of targets in the dataset, a quantitative assessment is difficult to achieve. We therefore chose the target pixels’ spectral values as the target signal and implemented this into 20 targets, which are located in four lines, with each line having four targets in a 200 x 200 scene. The positions of the implanted targets are shown in Fig. 3. The four targets in each line have sizes of 2 x 2, 1 x 2, 1 x 1, and 1 x 1, respectively. In other words, the targets in the same column are all of the same size. The synthesizing method is adding the target signal into the predefined position by the following equation: $t = b \times (1 - pec) + t \times pec(16)$, where $b$ and $t$ are the background and target spectra, respectively, and $pec$ is the mixing percentage. White noise with a SNR of 30:1 was also
obvious false alarms. A more reliable comparison needs to resort
detector based methods. In addition, (a), (e), and (i) present some
ground pixels in (b) and (f) than in the rest of the multiple-
detection result image, respectively. The other multiple-detector
the targets and background are the values of 1 and 0 in the
results of the single-detector AMSD and ACE are both segmented
3.2.1. Experimental results and analysis
The detection results are given in Fig. 4, where the detection
results of the single-detector AMSD and ACE are both segmented
by a threshold corresponding to 100% detection, so the values of
the target percentage is 0.1%. In the experiments, only half of the
target pixels are used as the training dataset to compute the
detection performance in the distribution construction and updating
procedures. All the targets are used for the test evaluation.

<table>
<thead>
<tr>
<th>Index of target in each line</th>
<th>Composition of target</th>
<th>Pixels’ structure (shape)</th>
<th>Filling factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>four pixel</td>
<td>A C</td>
<td>A: 30%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B D</td>
<td>B: 40%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>C: 60%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>D: 100%</td>
</tr>
<tr>
<td>2</td>
<td>two pixel</td>
<td>A</td>
<td>A: 50%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B</td>
<td>B: 100%</td>
</tr>
<tr>
<td>3</td>
<td>one pixel</td>
<td></td>
<td>50%</td>
</tr>
<tr>
<td>4</td>
<td>one pixel</td>
<td></td>
<td>100%</td>
</tr>
</tbody>
</table>

added. The last two targets in each line are of the same size but
with different percentages of target signal. The percentages of
target signals in each target are detailed in Table 3, with the
corresponding positions plotted in Fig. 3. For this AVIRIS dataset,
the target percentage is 0.1%. In the experiments, only half of the
target pixels are used as the training dataset to compute the
detection performance in the distribution construction and updating
procedures. All the targets are used for the test evaluation.

3.2.1. Experimental results and analysis
The detection results are given in Fig. 4, where the detection
results of the single-detector AMSD and ACE are both segmented
by a threshold corresponding to 100% detection, so the values of
the targets and background are the values of 1 and 0 in the
detection result image, respectively. The other multiple-detector
based methods present detection frequency images, so a larger
value suggests a higher probability of target occurrence. It can be
seen that the target pixels are more separable from the back-
ground pixels in (b) and (f) than in the rest of the multiple-
detector based methods. In addition, (a), (e), and (i) present some
obvious false alarms. A more reliable comparison needs to resort
to a quantity analysis. Further investigation requires a comparison
between the target pixels’ and the background pixels’ value
distribution. Here, the receiver operating characteristic (ROC)
curve is employed, since it provides a threshold-free performance
comparison by means of continuous curves in the detection
probability/false alarm domain [2].

From the ROC curves in Fig. 5, it is revealed that at the low-
value range of the false alarm axis, the different curves are not so
separable, except for DSD_{ACE}. In other words, the algorithms
perform similarly on the easy targets’ pixels, which are the ones
with a higher target signal percentage. In addition, the covariance-
based detectors have a slightly higher detection curve than the
subspace-based detectors. For example, ACE lies above AMSD
under a lower false alarm range. As the false alarm rate increases,
the curves are more complex. Detailed analysis of these curves
reveals that (1) the difference between mACE and mAMSD is much
smaller than that between single ACE and AMSD; (2) vDSD_{AMSD}
lies under DSD_{AMSD}, while vDSD_{ACE} is inseparable from DSD_{ACE}
at most ranges; (3) mACE has a better curve than ACE but is
obviously poorer than DSD_{ACE}; (4) mAMSD is also superior to
single AMSD but worse than DSD_{AMSD}; (5) mAMSD is very similar
to mACE, and is even better than mACE in some areas; (6) the
difference between DSD_{AMSD} and vDSD_{AMSD} is larger than that
between DSD_{ACE} and vDSD_{ACE}; and (7) DSD_{GLRT} performs better
than GLRT and mGLRT. The above situation is analyzed and is
concluded in the following.

Firstly, all the multiple-detector based algorithms give better
performance than their counterpart single-detector algorithms.
Meanwhile, the DSDs (DSD_{AMSD} and DSD_{ACE}) perform best among
all the detectors, which suggests that DSD is able to choose the
preferable samples for both subspace constitution and covariance
statistics.

Secondly, mAMSD exploits the separability between targets
and background better than single AMSD. This is a clue to the fact
that a more reasonable subspace structure does not consist of all
the pixels, but rather the locally chosen pixels [53,54]. In addition,
the fusion of multiple AMSD detections suppresses the probable
false alarms; the improved ROC curve is an important proof
of that.

Thirdly, the manifold learning anomaly exclusion procedure
introduced in vDSD_{AMSD} is more effective than in vDSD_{ACE}, or the
subspace-based detection method is more susceptible to anom-
aliesthe manifold. Furthermore, to separate targets from the
background subspace, more representative pixels are suitable for
the rational subspace construction. Meanwhile, by randomly
selecting blocks of pixels and then joining them together to get
the background information, more robust detectors can be con-
structed as both local and global information can be considered.
However, gathering local and global features has a greater effect
on the subspace model than the background covariance model.

Finally, it is revealed that both the subspace-based and
covariance-based DSD detection algorithms give a reasonable
performance. Therefore, it is inferred that whatever basic detector
is used, the proposed random dynamic subspace strategy increases
the separability between targets and background.

3.2.2. Parameter sensitivity analysis
The various parameters are investigated, and when investigat-
ing one parameter, the remaining ones are fixed. As GLRT is also a
covariance-based method, like ACE, only AMSD and ACE are used
in this part to analyze the parameters’ influence. One important
parameter in our method is the fusion criterion for the final
detection results. Two different fusion strategies are studied here.
One is “majority voting” (MV), and the other is “overwhelming
labeling”, which have been described in Section 2.3. Here, the
The number of false alarms under the 100% detection probability for these algorithms is investigated, and is presented in Figs. 6 and 7. “Frequency” means the rate of occurrence in all the detection procedures. After all the detection procedures are performed, all the detected probable target pixels in the procedures are considered in the detection fusion procedure. We calculate the rate of occurrence in all these procedures for each detected pixel, and the pixels with an occurrence rate larger than a predefined percentage are finally judged as target. This predefined percentage is defined as the “frequency of fusion”. Several different frequencies for the overwhelming number of occurrences are included, and the frequencies are converted into fractions. From Figs. 6 and 7, it is shown that as the frequency increases beyond half the number of all the detection procedures, which is also the same value in MV, the false alarms are restrained to a slightly lower range. As the frequency goes on increasing, the false alarms begin decreasing...
slowly, but the detection performance also declines. The tradeoff frequency is at 0.57. Here, “tradeoff frequency” refers to the critical value, and when the predefined frequency used in the fusion procedure is larger than this value, the detection begins to decrease remarkably, while no reduction in false alarms is apparent. In other words, to achieve the best detection results, the frequency should be no larger than this value. However, since the MV result is similar to the optimal one, and the optimal frequency is highly dependent on the particular dataset, with the pre-learning information required, the MV strategy is more practical and preferable. When DSDAMSD is taken into consideration, the same conclusion can be drawn.

Another parameter having an influence on the DSD methods is the segmentation value in each detection procedure to obtain the target occurrence images for the final fusion procedure, where the same threshold is used. It has been shown in the first section that the segmentation value used in our method is actually the percentage of the top value in the detection results. Based on the experimental data, three groups of percentage values are investigated, with each group having different levels. A low level corresponds to a comparable percentage to the real number of targets, a middle level corresponds to a double percentage, and a high level corresponds to a triple percentage. The number of false alarms under the best detection is also used as the evaluation criterion. Detailed information and the corresponding results are presented in Fig. 8. The columns filled with oblique lines suggest that the detection probability does not reach its best (under 100%). From Fig. 8, it is shown that a middle level percentage with a near 0.2% interval performs best.

Like the multiple classification system, the number of basic detectors, or the detection procedure, is an important factor as it influences the different land objects’ separability. Therefore, we now look at the varying number of basic detectors and the subsequent experimental results. The CFAR (constant false alarm rate) property is used here for the evaluation. In detail, the detection probability under the false alarm density of $5 \times 10^{-4}$ is
used as the reference. Fig. 9 presents the different cases under different numbers of detection procedures. DSD\textsubscript{ACE} and DSD\textsubscript{AMSBD} gave similar results, so the performance of DSD\textsubscript{ACE} is shown as an example. As the number of detections approaches 20, the detection curve becomes steady. The curve even begins to decrease as the number continues to enlarge. It is shown that when all the detection procedures contain nearly half of the pixels, the curve reaches its optimal point. Lee et al. [32] also revealed that approximately half of the bands constitutes an optimal subspace for classification. However, for hyperspectral image target detection, this number should be determined by considering the complexity and diversity of the ground objects for the particular image. It therefore depends on the different datasets used. Another point that needs attention is that due to the iterative procedure, the time cost of DSD is comparatively large. In this experiment, taking ACE as an example (with MATLAB 2010R software, a 2.53 GHz CPU frequency and 4 GB memory), the time costs for the datasets of ACE, mACE, vDSD\textsubscript{ACE}, and DSD\textsubscript{ACE} are approximately 7, 132, 151, and 171 s, respectively. In other words, the iterative-based DSDs are time consuming. More work will be done to accelerate the DSD algorithms in our future research.

3.3. Real-world dataset experiment I

From the above analysis, the experimental settings can be determined for the following two real-world datasets. For each image, the experiments are carried out with target training pixels to choose the most suitable background pixels to construct the detectors. The number of the detection procedures is defined as 12. The fusion strategy is majority voting. The segmentation value in each detection procedure is 0.2%. The first real-world dataset used is the HyMap hyperspectral image obtained from the Digital Imaging and Remote Sensing (DIRS) Laboratory website [55, 56]. It consists of a self-test image and a blind-test image. Due to the availability of the ground truth, the self-test image is used here. In addition, the dataset of the self-test image includes a library of target spectral reflectance, regions of interest, and ground photos. It was acquired by the airborne HyMap hyperspectral sensor at Cooke City, MT, US, in 2006. The spatial resolution is approximately 3 m, and it has a total of 126 spectral bands covering the VNIR–SWIR range (453–2496 nm), with a pixel size of 800 × 280. The ground scene covers a small town and near-town forest and grass areas. The reference to the ground truth for this dataset is available in [55]. Basically speaking, the area contains many different kinds of ground objects, so the according image is complex. Several different kinds of targets are deployed, including fabric panels and vehicles. The region of interest (ROI) dataset indicates the target positions, where the border pixels may be spectrally mixed by different materials [57]. The false color picture of the image is presented in Fig. 10. The area containing the targets is shown in Fig. 11. The area contains several fabric panels, with only three of the fabric panels used as targets in our experiment.

![Fig. 9. Influence of the number of detections.](image)

![Fig. 10. False color picture of the HyMap dataset.](image)

![Fig. 11. HYMAP hyperspectral dataset. (a) Sub-image and targets’ ROIs, (b) target and background spectra and (c) scene picture of target panel F1.](image)
The chosen target pixels for detection reference are shown in Fig. 11(a), with a total of 59 target pixels. For this HyMap dataset, the target percentage is about 0.26%. In the experiment, only half of the target pixels are used as the training dataset to compute the detection performance in the distribution construction and updating procedures. All the targets are used for the test evaluation. Fig. 11(c) shows the scene picture of one panel from a camera.

The detection results are evaluated by ROC curves, as shown in Fig. 12. It is clear from Fig. 12 that all the multiple-detector algorithms output a smaller number of false alarms than the single-detector algorithms under the same probability of detection. This phenomenon is more obvious when the false alarm rate is around $10^{-3}$. A higher false alarm rate corresponds to a lower threshold to segment the unresolved target pixels. Overall, the multiple-detector algorithms are more effectual than the single-detector algorithms on those more difficult target pixels. Furthermore, the DSD algorithms perform best among all the algorithms: mAMSD performs better than mACE and mGLRT at a higher false alarm rate, while vDSDACE gives better results than vDSDAMSD and vDSDGLRT. It is therefore concluded that the proposed multiple iterative detection is more promising than the multiple-detector methods, especially with ACE as the base detector. Meanwhile, DSDAMSD seems to present a very similar performance to DSDACE, which is unlike the case of AMSD and ACE. The reason for this may be that the target sizes are smaller than the spatial resolution of the image, and the pixels fit the linear mixture model, so that the separability between target and background signals can be better described by a subspace-based detector than the covariance-based methods. Furthermore, AMSD and ACE’s background statistics are both contaminated by included targets, so only with the dynamic subspace strategy can the detector’s representation ability for the background be fully used.

The separability analysis of the detection results is now discussed. The value ranges of the target pixels and the background pixels are shown in Fig. 13, where all the results have been normalized to [0, 2]. To make the comparison more distinct, a group of boxes are used, where the main body of a box indicates the majority of the pixels’ value range, with the overlapping area between the background and target boxes usually causing the false alarms. Although some detection methods can present a large overlap between the targets’ and backgrounds’ value ranges in the detection results, most targets lie far away from the background, in which case the separability between most targets and background is still promising. Therefore, a better detector will present a larger gap between the targets’ box and the backgrounds’ box. From Fig. 13, it is found that in spite of the similar false alarm rate under 100% detection in most cases in Fig. 12, the overlapping range in DSDAMSD is actually smaller than those of DSDACE and DSDGLRT. In addition, DSDAMSD also has more targets distributed in the higher range than DSDACE and DSDGLRT do. In other words, DSDAMSD does project the target and background signals into more compact and distinct ranges. When the number of targets is large, this advantage will present fewer false alarms and, in this case, the structured detectors may offer better performance than the unstructured detectors. Although the unstructured detectors use the background whitening processing, the more accurate descriptive information requires more pure background statistics, making it more sensitive to a little deviation.

Although the multiple-detector methods also use a manifold analysis to exclude the contamination of the subspace construction, they actually perform a little worse than the DSD detectors without manifold analysis. It is therefore concluded that our dynamic block method does play a role. However, it is also the truth that the DSD methods with manifold analysis are clearly better than the DSD methods without manifold analysis. The reason for this is that the block-wise selection strategy cannot avoid selecting target and spectral anomaly pixels for the background subspace construction, due to the large size. These pixels will present a larger reconstruction error due to their lack of neighbors in the manifold feature space. Therefore, the subsequent manifold analysis helps exclude them from the background dataset. In summary, it is the combination of the block-wise dynamic subspace and the manifold analysis that enables our proposed method to outperform the other methods. The same conclusion can also be drawn from Fig. 5.
As to the time cost, the single basic detectors, AMSD and ACE, take around 6 and 5 s, respectively; mAMSD and mACE take 112 and 92 s, respectively; vDSDAMSD and vDSDAEC take 121 and 110 s, respectively; and DSDAMSD and DSDACE take 145 and 131 s, respectively. GLRT takes 5.8 s; mGLRT takes around 117 s; and vDSDGLRT and DSDGLRT take 131 and 123 s, respectively. Therefore, DSD takes a comparable time to the multiple-detection procedures, but presents a much better performance.

3.4. Real-world dataset experiment II

To further investigate our proposed approach, another real-world AVIRIS hyperspectral image is utilized. This dataset covers a suburban scene in which there are three planes occupying 58 pixels as targets to be detected. In the experiment, only half of the target pixels are used as the training dataset to compute the detection performance in the distribution construction and updating procedures. All the targets are used for the test evaluation. Several kinds of background classes lie in the scene, including different roofs, roads, trees, grass, and shadow. The false color composite picture of the image dataset is shown in Fig. 14(a). The target positions are presented in Fig. 14(b). The spectral signatures of both the background classes and targets are shown in Fig. 14(c). The original band number is 224. The size of the image dataset is $200 \times 200$. However, some bands contain no signals, so these bands were removed, with only 189 bands remaining. The spatial resolution is about 4 m per pixel. Detecting the plane pixels from this dataset is difficult since the background objects are complex, including many different types of roof, with some kinds of roof being spectrally similar to the targets. In other words, these roof
pixels have a high probability of being detected as false alarms. Furthermore, due to the limited spatial resolution, many pixels of the planes are mixed pixels, especially those on the borders of the planes, which are composed of metal spectra corresponding to the plane, and cement spectra corresponding to the airport runway. These mixed pixels present a variable spectrum compared with a pure target spectrum, which makes them difficult to separate from the background objects. The previous experiments evaluated the performance of DSD with AMSD and ACE as the basic detectors. In this experiment, AMSD, ACE, and GLRT [14] are used as the basic detectors, and their multiple and DSD versions are employed to make a comparison.

The color density maps of the detection probability results for these algorithms are shown in Fig. 15. As the multiple-detector methods’ results are visually similar to DSD, only DSD’s results are presented. From Fig. 15(a), it can be observed that although the single basic detector AMSD is able to highlight some plane pixels, mainly the central pixels on the plane, which are colored red, most of the border pixels on the planes are indistinguishable from the background objects.

However, DSDAMSD highlights nearly all the plane pixels to a much higher value range, with all the plane pixels colored red, while the background pixels are suppressed into a low range, with a color nearer to blue, as shown in Fig. 15(d). In Fig. 15(b), ACE presents fewer false alarms than AMSD; however, the most highlighted pixels there are certain roof pixels, not the plane pixels. In Fig. 15(d), at the same time, DSDACE performs better in separating targets from the background, since all the pixels colored red lie on the planes. When GLRT in Fig. 15(c) and DSDGLRT in Fig. 15(f) are considered, this phenomenon is more obvious. GLRT would present a comparatively large false alarm rate since so many pixels have a color near to red in Fig. 15(c); however, DSDGLRT succeeds in suppressing these pixels and projecting the target pixels, as shown in Fig. 15(f). All in all, no matter how the original single basic detector performs, its counterpart DSD method always presents a significantly improved performance.

Furthermore, in order to objectively present a qualitative analysis of these different methods, ROC curves are presented in Fig. 16. Combining Figs. 15 and 16, several observations can be made. Firstly, all the DSD methods present a better performance than their counterpart basic methods and the multiple versions, presenting a higher detection probability, usually with a fixed false alarm rate. Secondly, although many background pixels reveal a higher value by a single basic detector, such as GLRT, by constructing a subspace from the iterative learning procedure, all the targets present higher separability from their backgrounds. Thirdly, all the DSD methods are indistinguishable from ACE at the low range of false alarm rate, so the DSD methods may not show an advantage in detecting pure target pixels. As the false alarm rate continues to increase, the DSD methods all lie above their counterpart single basic detectors (see Fig. 16). A higher false alarm rate corresponds to the case that these hard-to-detect mixed targets can be segmented. Thus, it is revealed that the DSD methods excel in separating the mixed-target pixels. Finally, DSDACE performs best among all the DSD methods. It can therefore be seen that the performance of the basic detector determines the rank of its corresponding counterpart. Considering the computational burden, a similar observation to the previous two experiments can be made: DSD takes much more time than the single basic detectors. However, the multiple detection procedures could be accelerated by a parallel computation environment, such as with a graphics processing unit (GPU). This will be the focus of our future work.

4. Conclusion

In this paper, a dynamic subspace detection (DSD) method is proposed which establishes a novel multiple-detector framework. The performances of different blocks of pixels in the hyperspectral image are evaluated and a corresponding performance analysis is calculated. Another procedure investigating the performances of datasets assembled with different numbers of blocks is also undertaken. Combining the two procedures with iterative pseudo-random processing presents datasets of certain blocks of pixels for each detection procedure. After elimination of the anomalous pixels by manifold analysis, the detection is performed. Finally, all the detection procedures’ performances are fused. Extensive experiments confirm the proposed method’s effectiveness with both simulated and real-world hyperspectral images. Several conclusions can be drawn: (1) the fusion of the results from multiple detection procedures helps in improving the detection performance; (2) the strategy of random selection and evaluation by the two nested detection performance distributions provides a simple and effective way of choosing the more reasonable pixels for subspace construction; (3) the locally chosen blocks of pixels, with different blocks distributed in distinct areas, suggests that the subspace should be constructed by local information, which consists of nearby pixels on the same patch in the manifold feature space; (4) the proposed framework is also effective in the covariance-based detection methods in the experiments, so it can be considered as a good way of constructing covariance information; (5) further exclusion of anomalous pixels with larger reconstruction errors by manifold analysis is useful to purify the representative pixels, and illustrates a more effective performance, especially for the structured detector based DSD.

Conflict of interest

None declared.

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References

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