Hyperspectral Remote Sensing Benchmark Database for Oil Spill Detection With an Isolation Forest-Guided Unsupervised Detector

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Abstract—Oil spill detection has attracted increasing attention in recent years, since marine oil spill accidents severely affect environments, natural resources, and the lives of coastal inhabitants. Hyperspectral remote sensing images provide rich spectral information which is beneficial for the monitoring of oil spills in complex ocean scenarios. However, most of the existing detection methods are based on supervised and semi-supervised frameworks to detect oil spills from hyperspectral images (HSIs), which require a massive amount of effort to annotate a certain number of high-quality training sets. In this study, we make the first attempt to develop an unsupervised oil spill detection method based on isolation forest (iForest) for HSIs. First, a Gaussian statistical model is designed to remove the bands corrupted by severe noise. Then, kernel principal component analysis (KPCA) is employed to reduce the high dimensionality of the HSIs. Next, the probability of each pixel belonging to one of the classes of seawater and oil spills is estimated with the iForest, and a set of pseudolabeled training samples is automatically produced using the clustering algorithm on the detected probability. Finally, an initial detection map can be obtained by performing the support vector machine (SVM) on the dimension-reduced data, and the initial detection result is further optimized with the extended random walker (ERW) model so as to improve the detection accuracy of oil spills. Experiments on hyperspectral oil spill database (HOSD) created by ourselves demonstrate that the proposed method obtains superior detection performance with respect to other state-of-the-art detection approaches. We will make HOSD and our developed library for oil spill detection publicly available at https://github.com/PuhongDuan/HOSD to further promote this research topic.

Index Terms—Extended random walker (ERW), hyperspectral image (HSI), isolation forest (iForest), oil spill detection.

I. INTRODUCTION

Oil spill detection has attracted increasing attention in recent years, since marine oil spill accidents severely affect environments, natural resources, and the lives of coastal inhabitants. Hyperspectral remote sensing images provide rich spectral information which is beneficial for the monitoring of oil spills in complex ocean scenarios. However, most of the existing detection methods are based on supervised and semi-supervised frameworks to detect oil spills from hyperspectral images (HSIs), which require a massive amount of effort to annotate a certain number of high-quality training sets. In this study, we make the first attempt to develop an unsupervised oil spill detection method based on isolation forest (iForest) for HSIs. First, a Gaussian statistical model is designed to remove the bands corrupted by severe noise. Then, kernel principal component analysis (KPCA) is employed to reduce the high dimensionality of the HSIs. Next, the probability of each pixel belonging to one of the classes of seawater and oil spills is estimated with the iForest, and a set of pseudolabeled training samples is automatically produced using the clustering algorithm on the detected probability. Finally, an initial detection map can be obtained by performing the support vector machine (SVM) on the dimension-reduced data, and the initial detection result is further optimized with the extended random walker (ERW) model so as to improve the detection accuracy of oil spills. Experiments on hyperspectral oil spill database (HOSD) created by ourselves demonstrate that the proposed method obtains superior detection performance with respect to other state-of-the-art detection approaches. We will make HOSD and our developed library for oil spill detection publicly available at https://github.com/PuhongDuan/HOSD to further promote this research topic.

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hence, it reduces the backscatter of the ocean surface, resulting in the appearance of dark spots in SAR images compared to the surrounding spill-free regions. For example, a generalized-likelihood ratio test-based edge detector was proposed based on SAR data to detect dark spots on the ocean surface [16], [17]. A polarimetric analysis framework was developed to analyze and compare the physical relationship between fully polarimetric (FP) and compact-polarimetric (CP) SAR architectures for ocean oil slick estimation. Experimental analysis shown that FP and CP SAR led to a similar performance while the $\pi/4$ mode performs the best in detecting oil slicks [18], [19]. These publications demonstrated that SAR data can be effectively applied for detecting oil spill areas on the ocean surface. However, a principal challenge of oil spill detection with SAR data is to identify the oil spill regions from other natural phenomena, since the darkened patches in the SAR image may be caused by grease ice, wind sheltering by land, internal waves, etc. [20]. Furthermore, the other limitations of SAR data are its high cost, low revisit frequencies, and relatively small swath widths. These limitations call for the development of the multiplatform SAR and other optical sensors, such as multispectral and hyperspectral sensors.

In addition to the SAR-based approaches, many studies have examined the feasibility of the multispectral image (MSI) for oil spill detection with high-level reliability. For instance, the moderate resolution imaging spectroradiometer (MODIS) instrument has been demonstrated to be effective in identifying oil spill regions due to relatively high spectral and temporal resolutions [21], [22], [23]. However, Landsat data with a higher spatial resolution have also been used to detect the oil spill regions by using the spectral and spatial information [24], [25], [26], [27]. Most of these oil spill detection methods are very analogous to the semantic segmentation task in computer vision, which relies on the labeled samples to learn a supervised classifier. However, MODIS data with 250 m resolution and Landsat with 30 m resolution may not meet the demand for fine oil spill identification of small regions, since the spatial resolution of the MSI data is greatly larger than the size of oil spill regions.

Hyperspectral sensors mounted on aircraft, an emerging technique in the remote sensing field, can provide both rich spectral and spatial resolutions. Such sensors can record hundreds of narrow spectral channels from the VIS to the IR wavelength. In recent years, this technique has been extensively applied in all kinds of aspects, such as object detection [28], [29], [30], retrieval of water constituents [31], [32], and mineral mapping [33], [34], [35]. Two types of oil emulsions, e.g., water in oil (WO) and oil in water (OW), were investigated with hyperspectral data, which have illustrated that feature bands at 1677 and 839 nm can be used to distinguish the WO and OW emulsions [36], [37]. However, machine-learning-based oil spill detection techniques with this type of data have also been developed, which was to find the spectral signature of the oil from the complex ocean environment, which could greatly decrease the false alarm rate of the oil spill regions [38], [39]. For example, in [40], [41], and [42], spectral shape matching methods were developed to achieve oil spill detection. Given a reference spectrum selected from the original image, the oil spill regions can be detected by matching the spectral curve shape of the selected spectrum and one of the observed spectra. In [7] and [43], deep-learning-based methods were introduced for oil spill detection, which can decrease the influence of the shadows and image noise, as well as increase the discrimination between the oil spill and the seawater. These approaches have been confirmed to be effective in identifying oil spill regions with a large number of training samples.

Nevertheless, there are still several challenges in achieving accurate oil spill detection with hyperspectral images (HSIs), which are presented as follows.

1) The Lack of Well-Annotated Public Oil Spill Dataset: Up to now, many oil spill detection approaches have been proposed in the remote sensing community, including machine learning algorithms and deep learning models. However, researchers often adopt a few HSIs to verify the effectiveness of the method, which may decrease the generalization ability of those approaches. Furthermore, those datasets are not available for other researchers, which cannot effectively promote the development of marine oil spill monitoring.

2) The Requirement of the Available Training Samples: Current hyperspectral oil spill detection approaches are based on supervised or semi-supervised learning manners, and thus, they highly rely on the availability of sufficient training samples. However, the collection of the high-quality training set is time-consuming and expensive because of the spectral variability caused by sun glint intensity, oil thickness, and oil emulsification stage, which leads to the fact that they cannot work in an unsupervised manner.

3) The Negative Effect of Image Noise: Due to the imaging environment, such as low lighting, shadow, and weather, the captured spectral bands in HSIs are usually corrupted by different degrees of noise, and the spectral bands with serious noise have a negative effect on the accuracy of the oil spill detection. In order to reduce the involvement of domain experts for the automatic detection of oil spill regions, the detection methods should have the capability to automatically decrease the interference of the severe noisy channels.

In order to overcome these issues, this article proposes an isolation forest (iForest)-guided unsupervised detector (IFUD) for oil spill detection of HSIs, in which the original HSI with severe noisy bands can be directly used as input. First, to alleviate the negative effect of the noisy bands, a Gaussian statistical-based method is developed to automatically remove the bands corrupted by serious noise. Then, the iForest method is performed on the dimensionality-reduced data so as to generate the pseudolabeled training samples. Next, the support vector machine (SVM) classifier is trained using these pseudolabeled samples, which have been produced automatically, to obtain an initial detection map. Finally, in order to further refine the detection result, the extended random walker (ERW) is adopted as the postprocessing step of the initial detection map, in which the interactions among adjacent pixels are fully exploited. Experiments performed on the hyperspectral...
Compared to previous studies, the novel contributions of the proposed oil spill detection method are concluded as follows.

1) We construct a novel hyperspectral remote sensing database, named HOSD, for oil spill detection, which is a publicly available benchmark dataset. To the best of our knowledge, this is the first public dataset for oil spill detection. Moreover, the dataset is of the largest scale on the total number of images. The building of this dataset will enable the research community to advance the state-of-the-art algorithms for oil spill detection.

2) Different from previous supervised oil spill detection methods which require the users to annotate the oil spill and seawater samples, we propose an unsupervised oil spill detection method based on iForest for the first time. Both the spectral and spatial information of oil spill regions are considered by the proposed method to automatically generate training samples for the spectral classifier.

3) The Gaussian statistical method is explored to estimate the noise level of each spectral band, and the bands contaminated with serious noise are automatically removed. Experimental results demonstrate that noisy band removal is beneficial for oil spill detection.

The rest of this work is summarized as follows. Section II gives the details of the proposed method. Section III depicts the study area and the constructed dataset. The comprehensive experiments performed on the constructed dataset are presented in Section IV, followed by an analysis in Section V. Finally, we summarize this study in Section VI.

**II. METHODOLOGY**

To automatically and efficiently detect oil spills using HSIs, we develop an unsupervised method based on iForest. As shown in Fig. 1, the proposed method mainly contains three steps. First, the noise variance of each band is estimated with the Gaussian statistical method, and the important channels are selected from the hundreds of spectral bands according to the noise level. Then, the number of selected bands is further decreased using the kernel principal component analysis (KPCA). Next, the iForest is employed to detect the probability of each pixel belonging to the oil film and the seawater, and the unsupervised clustering method is used to construct the positive and negative samples. Finally, the training set is fed into the SVM classifier to yield the initial detection map, and the ERW algorithm is utilized to optimize the initial detection map by integrating the spatial information so as to produce the final result. The detailed steps of the proposed approach are depicted in Sections II-A–II-C.

**A. Noisy Band Removal and Dimension Reduction**

Due to the sensor instability, calibration error, and photon effects, the captured HSIs often suffer from noise contamination, which seriously degrades the quality of HSIs and has a negative effect on image interpretation, such as object identification and image classification [44]. In the hyperspectral image classification community, a common strategy is to manually remove the bands corrupted by severe noise, and then the remaining bands are used for the subsequent tasks [45]. However, this band selection manner is time-consuming because of the high spectral dimension of hyperspectral data. To alleviate the issue, in this article, we develop an automatic band selection method based on the Gaussian statistical model to eliminate the severe noise bands. The band importance is first evaluated, and then the spectral bands with low noise variance are chosen based on an adaptive thresholding method. Specifically, the Gaussian statistical model is exploited to measure the noise level of different spectral bands. The noise variance of each spectral band is calculated by

$$\sigma_n = \sqrt{\frac{\pi}{2} \frac{1}{6(I_W - 2)(I_H - 2)} \sum_{i,j} |I_n(i,j) * M|}$$

for $n = 1, 2, \ldots, I_N$ (1)
where \( I_W \) and \( I_H \) stand for the spatial dimensions. \( I_N \) is the total number of spectral channels. \( \sigma_n \) is the estimated noise variance of the \( n \)th spectral band. \( \mathbf{M} \) is an image mask, i.e., the Laplacian operator, which is used to estimate the amount of noise in local region

\[
\mathbf{M} = \begin{bmatrix}
1 & -2 & 1 \\
-2 & 4 & -2 \\
1 & -2 & 1
\end{bmatrix}.
\]

(2)

Accordingly, the noise level of different bands is calculated by (1), which measures the importance of spectral bands with respect to oil spill detection. Next, the bands contaminated with serious noise can be easily determined and removed by using a threshold. The spectral bands with noise variance less than the threshold are preserved for the subsequent identification

\[
S_n = \begin{cases}
I_n, & \text{if } \sigma_n < \frac{1}{2N} \sum_n \sigma_n \\
\phi, & \text{Otherwise.}
\end{cases}
\]

(3)

Although the selected bands are more useful for identifying oil spill regions, the spectral dimension of the selected channels is still high. In addition, the spectral separability of pixels between seawater and oil film in the obtained data is relatively low. In order to improve discriminative capabilities for identifying oil spill regions and decrease the computing cost spent in the following operations, KPCA [46] is utilized to fuse the spectral dimension of the selected data. Specifically, the selected data \( \mathbf{S} = \{s_1, s_2, \ldots, s_m\} \in \mathcal{R}^{I_N} \) are first projected into high-dimensional feature space \( \mathcal{H} \) by using a kernel function \( \Phi : \mathcal{R}^{I_N} \rightarrow \mathcal{H} \), where the radial basis function kernel is adopted. Then, the kernel principal components can be obtained

\[
\mathbf{K} \alpha = \lambda \alpha \quad \text{s.t. } \| \alpha \|_2 = \frac{1}{\lambda}
\]

(4)

where \( \mathbf{K} \) denotes the Gram matrix \( \Phi^T(\mathbf{S})\Phi(\mathbf{S}) \). In this work, the selected bands \( \mathbf{S} \in \mathcal{R}^{I_N} \) are projected into \( \mathbf{Y} \in \mathcal{R}^{D} \). In this work, we refer the KPCA with \( \mathbf{Y} = \text{KPCA}(\mathbf{S}, D) \), where \( D \) is the number of bands.

B. Generation of Training Samples

Supervised detection approaches usually require a certain number of training samples for different classes. However, human labeling is time-consuming and an expensive task [47]. To alleviate this issue, we propose an automatic scheme for producing the training set instead of manual interpretation. By comparing the spectral curves of oil film and seawater, it is found that the spectral value of oil film is different from the surrounding seawater. Therefore, the spectral pixels belonging to oil film are easier to be distinguished than the seawater. Based on this observation, the iForest is adopted to obtain the probability of each pixel.

The iForest is proposed [48] for identifying outliers in machine learning, which has been widely used in image processing. The iForest is based on an assumption that the outliers are often more susceptible to be isolated in a given data, and thus the probability value of the same object tends to be the same. In oil spill detection, due to the spectral difference between the oil film and the seawater, the oil film is also easily isolated. Accordingly, the probability value belonging to oil film or seawater is also larger. Specifically, the automatic generation of training samples is described in detail in the following.

1) iForest Construction: The obtained dimension-reduced data \( \mathbf{Y} \) are used to construct the iForest. \( \mathbf{Y} \) is transformed into two dimensional matrix \( \hat{\mathbf{Y}} \in \mathcal{R}^{D \times N} \), where \( D \) and \( N \) denote the total number of bands and pixels, respectively. In order to construct the iForest, first, it is necessary to randomly choose \( K \) pixels from \( \hat{\mathbf{Y}} \) and divide the selected pixels into two child nodes, i.e., left node and right node. The pixel value smaller than the split value is divided into the left node, and the pixel value larger than or equal to the split value is divided into the right node. Here, the split value is stochastically chosen between the maximum value and maximum value of \( \hat{\mathbf{Y}} \). Then, the child nodes are recursively performed until one of the following condition is met: 1) the quantity of pixels in each child node is 1; 2) the tree reaches the maximum height \( H_{\text{max}} \); and 3) the pixels in each child node are the same. In this work, \( H_{\text{max}} = \log_2 K \) is regarded as the default parameter. Finally, the construction of isolation tree is repeated \( T \) times to obtain the iForest, where \( T \) is a free parameter.

2) Probability Calculation of Each Pixel: In this step, the constructed iForest is used to estimate the probability value of each pixel. In more detail, for each isolation tree, the path length \( h(x) \) of a pixel \( x \) is the quantity of edges that the pixel passes through in an isolation tree from the root node to the terminating node. Since the oil film pixels are always different from the surrounding seawater, they are easily isolated to the terminating node compared to seawater pixels. In this situation, the oil film pixels incline to have shorter path lengths in the isolation trees, and the path length is considered as a measure to obtain probability value of each pixel. It should be mentioned that the path length of each pixel in different isolation trees varies. Therefore, the final path length is produced by calculating the average path length of all isolation trees. Assume that the constructed iForest has \( T \) isolation trees, and \( h_i(x) \) is the path length of a test pixel \( x \in \hat{\mathbf{Y}} \) in the \( i \)th isolation tree, the average path length \( A(h(x)) \) on \( T \) isolation trees can be obtained

\[
A(h(x)) = \frac{1}{T} \sum_{i=1}^{T} h_i(x).
\]

(5)

Accordingly, the probability value \( p \in (0, 1] \) of the test pixel \( x \) is calculated

\[
p(x) = 2^{-A(h(x))}
\]

(6)

where \( c(m) = 2H(m - 1) - ((2(m - 1))/m) \), \( H(m) \) denotes the harmonic number estimated by \( \ln(m) + 0.5772156649 \) (Euler’s constant). After performing the same above-mentioned steps to each pixel of \( \hat{\mathbf{Y}} \), the probability map \( \mathbf{p} \) can be obtained.
3) Clustering: Since the probability of the same object, i.e., oil film or seawater, tends to be the same, the label of each pixel can be decided by using a clustering method, where the number of clusters is 2, i.e., the label of oil film \( L_o \) and the label of seawater \( L_s \). It should be mentioned that if the scene has other objects, such as boats and islands, we can first extract the water area and then perform the proposed method. In this study, an efficient \( k \)-means algorithm is performed on the probability map \( p \) to generate the training samples \( T_r = \{ L_o, L_s \} \).

C. Oil Spill Detection and Optimization

Given training samples \( T_r = \{ L_o, L_s \} \) and the dimension-reduced data \( Y \), a widely used spectral classifier, i.e., SVM, is employed to produce the initial detection map \( O \in \mathbb{R}^{t \times t} \), in which 1% of the whole training samples are randomly selected from \( T_r \) instead of using all available samples to avoid high computing cost. Here, the SVM is carried out with a library for support vector machines (LIBSVM) library [49], which is a Gaussian kernel classification algorithm that allows one to process high-dimensional data. The parameters in the SVM are decided using fivefold cross validation.

Since the SVM is a pixelwise classifier without considering any spatial information, the probability map obtained by SVM often looks very noisy. Due to the fact that the pixels in oil film and seawater areas are usually highly correlated in the spatial location, this article introduces the ERW method for refining the initial probability \( O \) to take full advantage of the available spatial information, since the ERW method not only removes the noisy pixels in the detection map but also ensures that the refined probability map can align well with real object boundaries [50]. Specifically, the refined probability maps for oil film and seawater regions are obtained by minimizing the following objective function

\[
E^t(P_t) = E^t_{\text{spatial}}(P_t) + \gamma E^t_{\text{aspatial}}(P_t)
\]

where \( t \) refers to different classes, i.e., oil film or seawater. The objective function in (7) consists of a spatial term and a aspatial term. The spatial term \( E^t_{\text{spatial}} \) is employed to characterize the spatial correlation among neighboring pixels while the aspatial term \( E^t_{\text{aspatial}} \) is used to model the spectral information of the input image

\[
E^t_{\text{spatial}}(P_t) = P_t^T L P_t
\]

where \( L \) is the Laplacian matrix of a weight graph,

\[
L_{ij} = \begin{cases} 
    e^{-\beta(v_i - v_j)^2}, & \text{if } i = j \\
    -e^{-\beta(v_i - v_j)^2}, & \text{if } i \text{ and } j \text{ are adjacent pixels} \\
    0, & \text{otherwise}
\end{cases}
\]

where \( v_i \) is the \( i \)th pixel value and \( \beta \) is the parameter. In this work, based on the analysis in the previous publication [50], the parameters \( \beta \) and \( \gamma \) in the ERW method are set as \( \gamma = 10^{-5} \) and \( \beta = 710 \) for all the experiments. The second term \( E^t_{\text{aspatial}} \) incorporates the initial probability maps \( O \) obtained by SVM, which is shown as follows:

\[
E^t_{\text{aspatial}}(P_t) = \sum_{q=1,q\neq t}^{N} P_t^T \Lambda_q P_t + (P_t - 1)^T \Lambda_t (P_t - 1)
\]

where \( \Lambda_t \) represents a diagonal matrix, in which the diagonal elements are composed of the initial probability maps \( O \).

Finally, the detection map \( \hat{C} \) is calculated by choosing the maximum of the refined probability maps \( P_t \)

\[
\hat{C} = \arg\max_t P_t
\]

where \( \hat{C} \) is the final detection result. According to the method descriptions presented earlier, Algorithm 1 summarizes the pseudocode of the proposed method.

Algorithm 1 Hyperspectral Oil Spill Detection Method

Input:
- Input hyperspectral image \( I \);

Output:
- Detection map \( \hat{C} \)

1: Begin
2: According to (3), remove the severe noisy bands from the input \( I \), so as to obtain noise removal data \( S \).
3: According to (4), reduce the spectral dimension of \( S \), so as to obtain the dimension-reduced image \( Y \).
4: Transform dimension reduced image \( Y \) into two-dimensional data, i.e., \( \hat{Y} \in \mathbb{R}^{D \times N} \).
5: According to (6), calculate the detection probability \( p_t \) of each pixel \( i \).
6: Construct the training set \( T_r = \{ L_o, L_s \} \) by performing the \( k \)-means algorithm on the probability map \( p \).
7: Classify the hyperspectral image \( I \) with the SVM classifier, so as to obtain the initial detection map \( O \).
8: According to (7), optimize the initial detection map \( O \) so as to obtain the final detection map \( \hat{C} \).
9: Return \( \hat{C} \)
10: End

III. DATASETS

A. Study Area

The study area is situated in the GM, North American continent, around 25° N and 90° W. As the biggest marine oil disaster in the US history on April 20, 2010, more than 200 million gallons of crude oil are released into the GM. To better monitor and clean up the oil spill, it is necessary to detect the oil spill region. Hyperspectral data, which provide rich spectral information from the VIS to the IR spectrum, are a good candidate for oil spill detection.

B. HOSD Database

According to the study area, we create a large-scale hyperspectral database with the airborne visible/infrared imaging spectrometer (AVIRIS) sensor from different test sites. The constructed database, called as HOSD, is the first public oil spill detection dataset, which can act as a data source.
to develop state-of-the-art approaches for oil spill detection. Compared with oil spill datasets used in other publications, HOSD has the advantages of wide distribution and large coverage, and it also contains the largest number of data. The reference maps of all studied sample images are manually annotated by using the environment for visualizing images (ENVI) software. The oil spill areas are labeled pixel by pixel under the guidance of the field experts. These datasets have been processed with an atmospheric correction model in ENVI 5.3 software before oil spill detection, where the fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) is adopted. Table I lists some features of the HOSD, which consists of 18 HSIs. The spectral coverage is from 365 to 2500 nm. Owing to different altitudes in different routes, the spectral coverage, and it also contains the largest number of data. The reference maps of all studied sample images are manually annotated by using the environment for visualizing images (ENVI) software. The oil spill areas are labeled pixel by pixel under the guidance of the field experts. These datasets have been processed with an atmospheric correction model in ENVI 5.3 software before oil spill detection, where the fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) is adopted. Table I lists some features of the HOSD, which consists of 18 HSIs. The spectral coverage is from 365 to 2500 nm. Owing to different altitudes in different routes, the spectral resolution of the images is also different. The HOSD is freely available for research purposes.

Table I

| Database | Spatial size | Resolution | Flight time |
|----------|--------------|------------|-------------|
| GM1      | 1200*633     | 7.6m       | 5/17/2010   |
| GM2      | 1881*693     | 7.6m       | 5/17/2010   |
| GM3      | 1430*691     | 7.6m       | 5/17/2010   |
| GM4      | 1700*691     | 7.6m       | 5/17/2010   |
| GM5      | 2042*673     | 7.6m       | 5/17/2010   |
| GM6      | 2128*689     | 8.1m       | 5/18/2010   |
| GM7      | 2302*679     | 3.3m       | 7/09/2010   |
| GM8      | 1668*550     | 3.3m       | 7/09/2010   |
| GM9      | 1643*447     | 3.2m       | 7/09/2010   |
| GM10     | 1110*675     | 7.6m       | 5/17/2010   |
| GM11     | 1206*675     | 7.6m       | 5/17/2010   |
| GM12     | 869*649      | 7.6m       | 5/06/2010   |
| GM13     | 1135*527     | 3.2m       | 7/09/2010   |
| GM14     | 1790*527     | 3.2m       | 7/09/2010   |
| GM15     | 1777*510     | 3.3m       | 7/09/2010   |
| GM16     | 1159*388     | 3.2m       | 7/09/2010   |
| GM17     | 1136*660     | 7.6m       | 5/17/2010   |
| GM18     | 1047*550     | 3.3m       | 7/09/2010   |

IV. EXPERIMENTS

To examine the effectiveness of the proposed method for oil spill detection, several state-of-the-art classification and detection methods are adopted for comparison, including a high-dimensional data clustering method, unsupervised classification methods, object detection methods, and a supervised oil spill detection method. For the high-dimensional data clustering method, a scalable exemplar-based subspace clustering (SESC) method [51] was adopted as a competitor, since it can obtain satisfactory clustering performance for high-dimensional and class-imbalanced data compared to other clustering methods. For the case of a hyperspectral unsupervised classification method, a representative unsupervised method derived from rank-two nonnegative matrix factorization (R2NMF) [52] was used as the comparison algorithm. For the case of the hyperspectral unsupervised object detection methods, a popular object detection approach based on low-rank and sparse matrix decomposition (LRSMD) [53] was employed to achieve the oil spill detection. Another recently proposed object detection method based on kernel iForest (KIF) [54] was considered for comparison purposes, because it shows state-of-the-art performance in object detection. For the supervised oil spill detection method, a PCA-based minimum distance (PCAMD) detection method [55] was used for comparison, in which 25 principal components were preserved and the number of training samples was 1% for oil film and seawater. The implementation of these approaches was achieved by using the publicly available codes. For all parameters of these approaches, we mainly comply with the recommendations of the authors in the related publications.

To objectively evaluate the detection performance of different approaches, two widely used objective indexes, i.e., area under curve (AUC) [56] and detection precision (DP) [57], for object detection are adopted.

1) **AUC**: Given a detection result and a reference map, the AUC is defined as

\[ \text{AUC} = \int_{-\infty}^{+\infty} \text{TPR}(H) \cdot \text{FPR}'(H) \cdot dH \]  

where the true positive rate TPR(H) measures how many true positive samples happen among all positive results, when the threshold for the detection result is H. FPR represents how many false positive samples happen among all negative results. The main superiority of the AUC index is that it relies only on the order of the pixels rather than absolute detection values.

2) **DP**: DP calculates the percentage of the true positives to the total number of positive samples, which is defined as

\[ \text{DP} = \frac{\text{TP}}{\text{TP} + \text{FP}} \]  

where TP and FP denote true positive and false positive, respectively. The higher the value of this index, the better the oil spill detection performance is.

A. Parameter Analysis

In this work, there are two parameters that are needed to be determined, i.e., the number of the fused data D and the number of isolation trees T. The sensitivity analysis of the two parameters is conducted on the HOSD dataset. When the number of the fused data D is discussed, the number of isolation trees T is fixed to 800. Fig. 2(a) and (b) shows the detection performance of the proposed method with different numbers of D. It can be observed that when D is 25, the proposed method yields the highest detection accuracies. In addition, Fig. 2(c) and (d) presents the detection performance of the proposed method with different numbers of T. It can be observed that the detection performance of the proposed method tends to be stable as T increases. When T is 800, the proposed method produces satisfactory detection performance. Based on this observation, D = 25 and T = 800 are considered as the default parameters in this article. The following experiments also illustrate that the proposed method indeed produces promising detection results with this parameter settings.

1https://github.com/PuhongDuan/HOSD.
B. Detection Results

The original images and detection results of different methods are presented in Fig. 3. By comparing the detection results, it can be observed that the object detection methods based on LRSMD and KIF cannot work well for oil spill detection. The LRSMD method can only detect a small amount of oil spill regions. The reason is that the Mahalanobis distance in the LRSMD method cannot well model the spectral difference between the seawater and oil film. By contrast, the KIF method exhibits a little improvement in terms of detection performance. However, this method produces very “noisy” resulting maps, and some images can hardly be identified, such as GM13, GM14, GM15, and GM16.

For the high-dimensional clustering method, the SESC method produces similar results with the KIF method. The oil film and seawater cannot be distinguished by spectral clustering. This is due to the low discrimination between seawater and oil film, and thus, it is difficult to effectively detect the oil spill regions from similar spectrum. This step is able to greatly boost the robustness of the proposed method. However, the detection results obtained by the proposed method are mainly due to several reasons: first, the noisy band removal can effectively alleviate the interference of severe noisy bands to detection performance. Second, the iForest method produces relatively true training samples, even though it does not involve human annotation. Third, the ERW-based optimization process takes full advantage of the spatial correlations among neighboring pixels. This optimization is beneficial for improving the detection accuracy.

Tables II and III give the objective results of the considered approaches on the HOSD database. It is obvious that the proposed method obtains competitive performance among all considered methods in terms of AUC and DP, which is consistent with the visual effects. The PCAMD method is better than the proposed method on five sample images. The reason is that the PCAMD is a supervised approach, in which the training set is directly chosen from the reference label. The preparation of training samples is time-demanding and requires a large amount of manpower. On the contrary, the proposed method aims to automatically obtain the pseudolabeled training samples, which is of high interest in real applications. Generally, it can be observed from Tables II and III that our method produces the highest detection accuracy compared to other approaches on the HOSD database.

C. Running Time

In this work, all experiments are conducted with MATLAB 2014a on a laptop with Intel (R) Core (TM) i7-6700 HQ CPU.
Table IV shows the running time of all detection methods. It is found that the PCAMD method performs the fastest, since it only employs simple distance to identify different classes. The running time of the KIF method is the highest among all considered approaches. The reason is that the iForest requires a large number of iterations to build the tree structures. In addition, the proposed method is computationally expensive than the PCAMD and SESC methods, while is much more efficient than the KIF method. Generally, the running time of the proposed method is acceptable. How to efficiently reduce the running time would be an interesting topic that is not the scope of this work.

V. DISCUSSION

A. Influence of the Bands Corrupted by Severe Noise

In this section, we discuss the influence of the bands corrupted by severe noise on the detection performance of the proposed method. Taking GM1 as an example, Fig. 4 shows the estimated noise level of each spectral channel. It can be observed that when the noise level is relatively larger, the spectral channel is corrupted by serious noise. Moreover, the bands contaminated with serious noise cannot provide rich scene information, such as band 1 and band 104. Therefore, it is essential to remove these spectral bands corrupted by serious noise, which benefits to improve the oil spill detection performance.
An experiment is conducted on the HOSD database with or without the bands corrupted by serious noise. The detection accuracy is shown in Fig. 5. Through comparing the experimental results, it is found that when the corrupted bands are removed, the detection accuracies obtained by the proposed method tend to increase. This experiment verifies the effectiveness of the Gaussian statistical method in automatically removing the bands contaminated by severe noise. Therefore, the proposed method is robust to corrupted bands.

B. Influence of the ERW Optimization

Due to the spectral similarity between different objects, the classification map obtained by the spectral classifier (e.g., SVM) usually contains the salt-and-pepper noise. The spatial information in HSIs can play a complementary role in reducing misclassification. This is mainly because of the fact that the pixels belonging to the same object are often adjacent in the spatial location. Here, we discuss the influence of the ERW optimization to oil spill detection accuracy. An experiment is conducted on the HOSD dataset. Fig. 6 gives the detection accuracies obtained by the proposed method with or without the optimization step. It is easy to observe that the proposed method without ERW optimization tends to decrease in terms of AUC and DP. This experiment illustrates that the ERW-based optimization is an effective scheme to reduce the influence of noisy labels.

VI. Conclusion

In this study, we developed an unsupervised oil spill detection approach for HSIs. The proposed approach, which is based on the robust iForest, demonstrates several attractive characteristics: 1) Hyperspectral data are often contaminated by noise, which downgrades the quality of the detection step. This article introduces a Gaussian statistical method to automatically remove the bands contaminated by severe noise. Therefore, the proposed method is robust to corrupted bands. 2) To decrease the involvement of human labor, this article proposes an automatic method based on the iForest to select training samples of the input data. Accordingly, it does not require manual labeling, which can be better applied in real applications. 3) This article makes full use of the spatial information among adjacent pixels, and thus, the “noise” in the detection maps can be greatly reduced and the detection performance is also improved.

In addition, we constructed a large-scale oil spill detection dataset, i.e., HOSD, with few images. The HOSD is a freely available dataset and can be used to achieve oil spill detection or train deep models. We have tested the performance of the proposed approach on the HOSD. Experimental results have confirmed that the proposed approach can outperform other advanced approaches including high-dimensional data clustering, unsupervised object detection methods, and supervised oil spill detection techniques. As future work, we would like to extend the proposed method to other marine disaster detection, such as red tide and Enteromorpha prolifera, through using the spectral difference. In addition, high-quality training set generation is worth to be further studied in the future development.

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