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Utilization of a Full Convolutional Autoencoder for the Task of Anomaly Detection in Hyperspectral Imagery

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Abstract

The advancement of artificial intelligence has significantly improved the capability to capture background features in hyperspectral images (HSI), thereby demonstrating commendable performance in the domain of hyperspectral anomaly detection (HAD). The existing approaches, however, still exhibit certain limitations: (1) The deep feature learning process lacks contextual, anomaly constraints, and prior information. (2) The priority reconstruction of the background cannot be ensured by traditional HSI anomaly detectors based on self-supervised deep learning. (3) The utilization of spatial information in hyperspectral images is limited by the fully connected deep network structure of the HSI anomaly detector. The performance of many hyperspectral anomaly detectors is limited by assumptions or presumptions regarding background and anomaly distributions, as these detectors cannot accurately account for the complex real-world distributions. The paper proposes a self-supervised full convolutional autoencoder as a solution to address these issues. The effectiveness and performance of the method were confirmed through evaluation on two real hyperspectral datasets, demonstrating superiority over nine other state-of-the-art methods.

Keywords: Hyperspectral Image Analysis, Anomaly Detection, Full Convolutional Autoencoder, Self-Supervised Learning

1. Introduction

The hyperspectral images encompass abundant spatial and spectral information. The hyperspectral remote sensors capture hyperspectral images by integrating two spatial dimensions into the image, along with an additional spectral dimension comprising hundreds or thousands of nearly continuous spectral curves that represent land cover. The utilization of high spectral resolution enables the dependable extraction of spectral characteristics, facilitating differentiation between distinct features. The utilization of hyperspectral images is prevalent in various domains such as target detection, classification, change detection, and other related fields. The hyperspectral anomaly detection (HAD) technique identifies abnormal targets in hyperspectral images by detecting pixels exhibiting distinct spectral curves and occupying a small spatial proportion. The abundance of spatial and spectral information in hyperspectral images facilitates the identification of anomaly targets, even without prior knowledge of their specific spectral features (Su et al., 2022).

The past two decades have witnessed the emergence of advanced models and methodologies for anomaly detection in hyperspectral remote sensing images. (Wang et al., 2023). The application of deep learning technology in the field of HAD has garnered increasing attention. (Hu et al., 2022). The most widely used approach for monitoring HAD is the utilization of CNND (Li et al., 2017). The Autoencoder (AE) models (Gao et al., 2023) and generative adversarial networks (GANs) are commonly employed for extracting the deep intrinsic spectral features of the Hang Seng. The AE model and GAN were first introduced into HAD by Arisoy et al., establishing them as pioneers in this field. The utilization of GANs in HADGAN (Jiang et al., 2020) enables potential feature layers to acquire knowledge regarding multivariate normal background distributions. The fully convolutional autoencoder (Auto-AD) for HAD was initially proposed by Wang et al. (2021), incorporating adaptive learning.

we propose a novel FCAE-HAD method. The proposed method makes the following contributions: (1) A novel fully convolutional autoencoder is proposed to effectively leverage spatial information for enhancing hyperspectral anomaly detection and achieving integrated anomaly detection with spatial structure. (2) The proposed deep network learning is guided by a prior knowledge extraction module that combines DBSCAN and connected component analysis clustering. This module extracts background samples and abnormal samples, ensuring a clear learning direction for the deep network. (3) A potential adversarial consistency network for feature extraction is proposed, which addresses the limitation of assuming a specific background distribution and achieves more accurate reconstruction of pure backgrounds.

2. Proposed Method

2.1. Overview

The unsupervised full convolutional autoencoder (FCAE) proposed in Figure 1 is illustrated.

2.2. The Extraction of Prior Knowledge through Bi-Clustering

The bi-clustering process employed in this study primarily encompasses two methodologies: DBSCAN clustering within the spectral domain and CCC clustering within the spatial domain. The DBSCAN algorithm is employed to cluster the spectral information. Specifically, a random pixel is selected as the initial point, and subsequently all pixels are iteratively examined to identify the core category graph $M_1 = \{m_i^1\}_{I=1}^{i=H\times W} \in \mathbb{R}^{H\times W}$. The results of our experiments demonstrate that, due to the overwhelming number of background events compared to anomalies, it is possible to generate up to 312 categories from the clustering outcomes. The binary classification map $P_1 = \{p_i^1\}_{I=1}^{i=H\times W} \in \mathbb{R}^{H\times W}$ is obtained at last as:

$$P_1 = \begin{cases} p_i^1 = 1, \cdot m_i^1 \in 1 \\ p_i^1 = 0, \cdots m_i^1 \notin 1 \end{cases} \tag{1}$$

The presence of isolated noisy pixels and background objects that significantly deviate from the surrounding backgrounds in a binary classification graph may lead to misclassification as anomaly objects. The problem at hand can be addressed by introducing a spatial clustering approach that leverages connected component analysis. The connected component labeled graph $M_2 = \{m_i^2\}_{I=1}^{i=H\times W} \in \mathbb{R}^{H\times W}$ is derived to represent the spatial relationship between the background and anomalies. The labels $P_2 = \{p_i^2\}_{i=1}^{i=H\times W} \in \mathbb{R}^{H\times W}$ we obtained are prominently bold as follow:

$$P_2 = \begin{cases} p_i^2 = 0, & m_i^2 \in L_2 \\ p_i^2 = 1 & m_i^2 \in L_1 \\ p_i^2 = 0 & m_i^2 \in L_1 \\ p_i^2 = 1 & m_i^2 \in L_3 \end{cases} \text{ and } \frac{L_1}{L} < 0.8 \tag{2}$$

The numbers L_1, L_2, and L_3 represent three types of connected components respectively. The total number of connected components is denoted as $L = L_1 + L_2 + L_3$. In summary, the filter associated with device L_1 exhibits superior detection performance while having minimal impact.

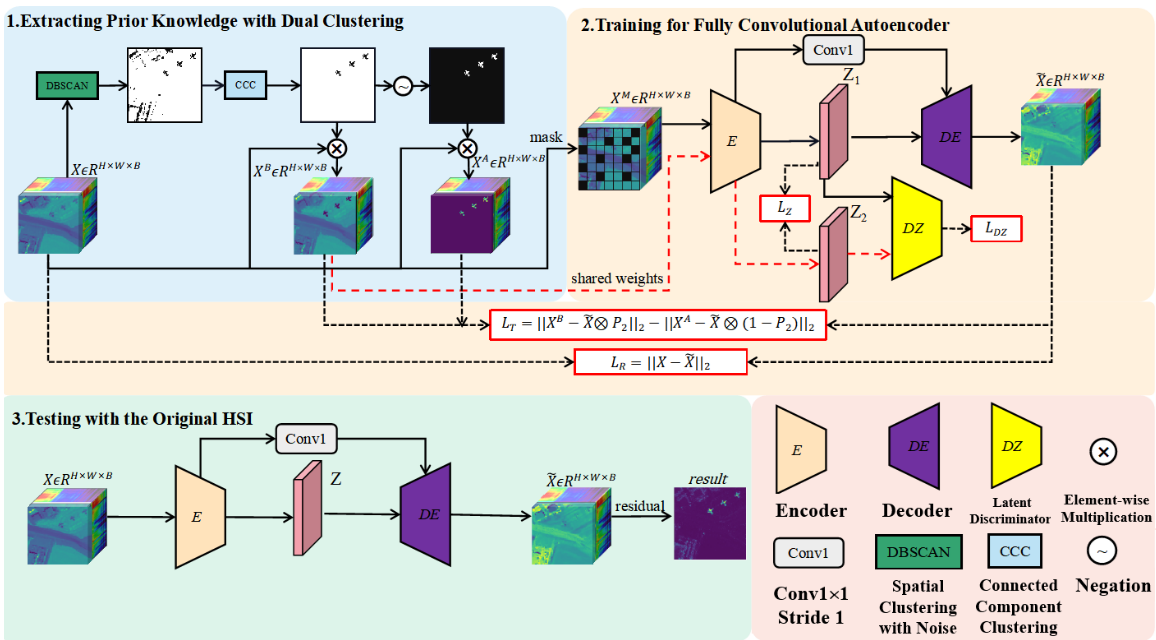

Figure 1: The proposed flow chart illustrates the FCAE-HAD method.

2.3. Training of Full Convolutional Autoencoders

The FCAE-HAD method leverages bi-clustering to extract prior knowledge. The proposed method introduces a robust approach for acquiring background features in a full convolutional autoencoder, based on the adversarial consistency network. The training stage will be divided into the following three distinct parts:

(1) The data is being incremented. The patch size is randomly selected from a predefined set of options in order to segment the original hyperspectral image into K different patch sizes. The task is to randomly select N patches, where $N < K$ and $0.3 < N/K < 1$, from the given K sizes. The position of these N patches is then correlated with the mask map S with a value (0 or 1), where 0 denotes the occluded area, 1 represents another pixel. The set $S = \{s_i\}_{i=1}^{i=H\times W} \in \mathbb{R}^{H\times W}$ is defined here. Considering the prevalence of the multivariate Gaussian distribution observed in the background, a generated mask is populated with a cube $I \in \mathbb{R}^{H\times W\times B}$ containing Gaussian noise. Here, $S = \{s_i\}_{i=1}^{i=H\times W} \in \mathbb{R}^{H\times W}$. The final deep network can be mathematically formulated as:

$$X^M = X \otimes S + I \otimes \bar{S} \tag{3}$$

(2) Network architecture. The network architecture of FCAE-HAD, as depicted in Figure 1. The FCAE employs convolutional autoencoders (CAE) to facilitate self-supervised learning of hyperspectral image (HSI) cubes. The distinguishing factor of our FCAE, as opposed to simple CAE. The coding process is outlined as follows:

$$\begin{aligned} F_1 &= \mathrm{SSAJ}\left(\mathrm{Conv}\,1\left(X^M\right)\right) \\ F_2 &= \mathrm{EresConvBlock}\left(\left(F_1\right)\right) \\ F_3 &= \mathrm{EresConvBlock}\left(\left(F_2\right)\right) \\ F_4 &= \mathrm{EresConvBlock}\left(\left(F_3\right)\right) \\ Z &= \mathrm{EresConvBlock}\left(\left(F_4\right)\right) \end{aligned} \tag{4}$$

The decoding process can be formulated as:

$$\begin{aligned} F_5 &= \mathrm{SSAJ}(Z) \\ F_6 &= \mathrm{DEresConvBlock}\left(\mathrm{Concat}\left(\mathrm{Upsampling}\left(F_5\right), \mathrm{Conv}\,1\left(F_4\right)\right)\right) \\ F_7 &= \mathrm{DEresConvBlock}\left(\mathrm{Concat}\left(\mathrm{Upsampling}\left(F_6\right), \mathrm{Conv}\,1\left(F_3\right)\right)\right) \\ F_8 &= \mathrm{DEresConvBlock}\left(\mathrm{Concat}\left(\mathrm{Upsampling}\left(F_7\right), \mathrm{Conv}\,1\left(F_2\right)\right)\right) \\ \tilde{X} &= \mathrm{Conv}\,1\left(\mathrm{DEresConvBlock}\left(\mathrm{Concat}\left(\mathrm{Upsampling}\left(F_8\right), \mathrm{Conv}\,1\left(F_1\right)\right)\right)\right) \end{aligned} \tag{5}$$

The spectral-spatial joint attention mechanism utilizes global maximum pooling in the spatial dimension and global average pooling in the spectral dimension.

The EResConvBlock is composed of three convolution layers: a 3×3 convolution layer, a 3×3 convolution layer, and a 1×1 convolution layer. The convolutional layers are supplemented with batch normalization and LeakyReLU activation functions for enhanced performance.

The DEResConvBlock consists of three 1×1 convolutional steps with a stride of 1 and one 3×3 convolutional step with a stride of 1, effectively enriching and enhancing the decoded feature representation. The convolutional layers are sequentially accompanied by batch normalization and LeakyReLU activation functions.

The Latent Feature Adversarial Consistency Network (LFACN) comprises an encoder and a discriminator for latent features. The input sample $X^M \in \mathbb{R}^{H\times W\times B}$ and the prior background sample $X^M \in \mathbb{R}^{H\times W\times B}$ are encoded by the shared weight encoder E, yielding the potential features Z_1 and Z_2 respectively. The encoder is augmented with a potential feature discriminator DZ to ensure the similarity of the background potential feature distribution, thereby minimizing the discrepancy between input potential feature Z_1 and hyperspectral image's potential feature Z_2. The reconstructed background $\tilde{X} \in \mathbb{R}^{H\times W\times B}$ obtained through E for coding should exhibit a higher degree of similarity to the prior background sample X^B, as indicated by its corresponding potential feature Z_3. The $L1$ loss function is employed to ensure the underlying feature consistency, as deep networks have limitations in guaranteeing this constraint.

(3) Learning Stage. The proposed deep network architecture comprises an encoder E, a decoder DE, and a discriminator DZ. The loss function comprises the adversarial loss, the triplet loss L_T,

adversarial consistency loss L_Z, and reconstruction loss L_R. The deep network model undergoes a comprehensive learning process, wherein the optimization of model parameters is achieved iteratively through gradient backpropagation, leveraging these four losses. The mean square error (MSE) serves as the reconstruction loss:

$$L_R = \|X - \tilde{X}\|_2 \tag{6}$$

The triplet loss utilizes two mean square errors, as depicted in the subsequent equation:

$$L_T = \left\|X^B - \tilde{X} \otimes P_2\right\|_2 - \left\|X^A - \tilde{X} \otimes (1 - P_2)\right\|_2 \tag{7}$$

The adversarial loss and adversarial consistency loss of encoder E and potential feature discriminator DZ can be expressed as follows:

$$L_{DZ} = \mathbb{E}\left(\log\left(DZ\left(Z_2\right)\right)\right) + \mathbb{E}\left(\log\left(1 - DZ\left(Z_1\right)\right)\right) \tag{8}$$

$$L_Z = \|Z_3 - Z_2\|_2 \tag{9}$$

Finally, the total loss can be expressed as:

$$L_{\text{all}} = \partial L_T + \beta L_Z + \mu L_R \tag{10}$$

The values of ∂, β, and μ are set to 0.9, 0.1, and 0.1 respectively, based on the task requirements. The network learning rate lr is 0.001. Once the training is completed, the parameters of the deep network remain fixed while utilizing them to reconstruct the original HSI.

2.4. Testing Stage

After optimizing and fine-tuning the parameters of the deep network $\hat{\theta}$, we eliminate the discriminator DZ and only retain the encoder E and decoder DE for hyperspectral image reconstruction. The raw HSI X is utilized for detection instead of the training mask image X^M, as it closely resembles real-world scenes. The trained model subsequently performs an end-to-end reconstruction of the background image. The trained model subsequently performs an end-to-end reconstruction of the background image X, as depicted below. as depicted below:

$$\tilde{X} = FCAE - HAD(X, \hat{\theta}) \tag{11}$$

The FCAE-HAD deep network proposed evolves into a robust background reconstruction network through the integration of bi-cluster and triple-loss guided learning, as well as adversarial consistency network training on real background data. Finally, the hyperspectral anomaly detection results are obtained by equation (12):

$$G_{i,j} = \|x_{i,j} - \tilde{x}_{i,j}\|_2 \tag{12}$$

The original HSI $X \in R^{H\times W\times C}$ and the refactored HSI $\tilde{X} \in R^{H\times W\times C}$ of the pixel are denoted as $x_{i,j} \in \mathbb{R}^{B\times 1}$ and $\tilde{x}_{i,j} \in \mathbb{R}^{B\times 1}$, respectively. The final test graph $G = \{G_{i,j}\}_{i=1,j=1}^{i=H,j=W} \in \mathbb{R}^{H\times W}$, is formed by assigning the abnormal pixel ratings to the corresponding positions (i, j).

3. Experiments

The experiment involved the testing of two authentic hyperspectral images. The scene in San Diego measures 100 x 100 with a total of 189 bands, while the scene in Pavia has dimensions of 150 x 150 and consists of 102 bands. The study conducted a comparative analysis of nine cutting-edge anomaly detection techniques, encompassing three advanced deep learning methodologies. The detection performance of LRBSN was comprehensively evaluated by presenting heat maps, visual ROC curves, and AUC indices for each method (see Figure 2, Figure 3, Figure 4, and Table 1). The results demonstrate the efficacy of the proposed method in detecting abnormal spatial structures. The ROC curve of our method consistently ranks among the top performers. The background suppression and prominence of our method surpass those of other methods.

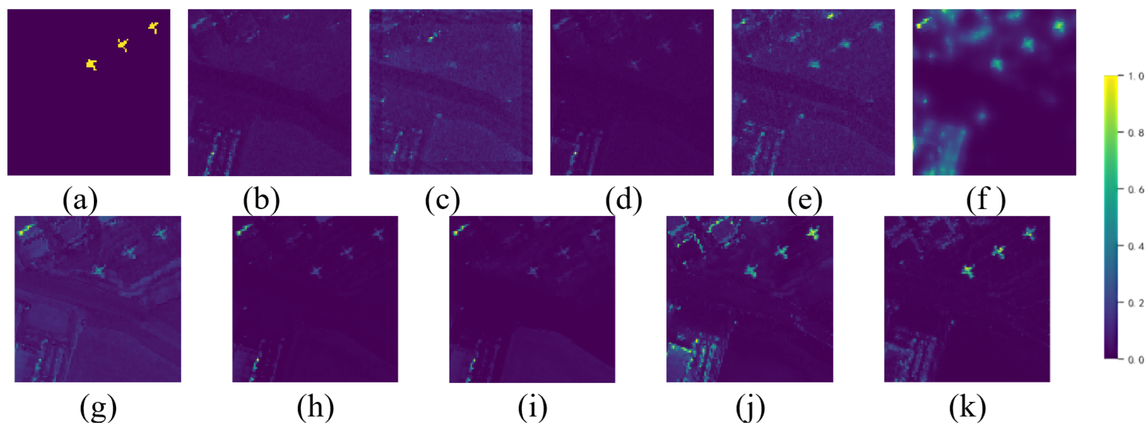

Figure 2: The heat maps of the San Diego dataset: (a) ground truth (b) GRX (c) LRX (d) FRFE (e) CRD (f) AED (g) LRASR (h) GAED (i) RGAE (j) Auto-AD and (k) ours.

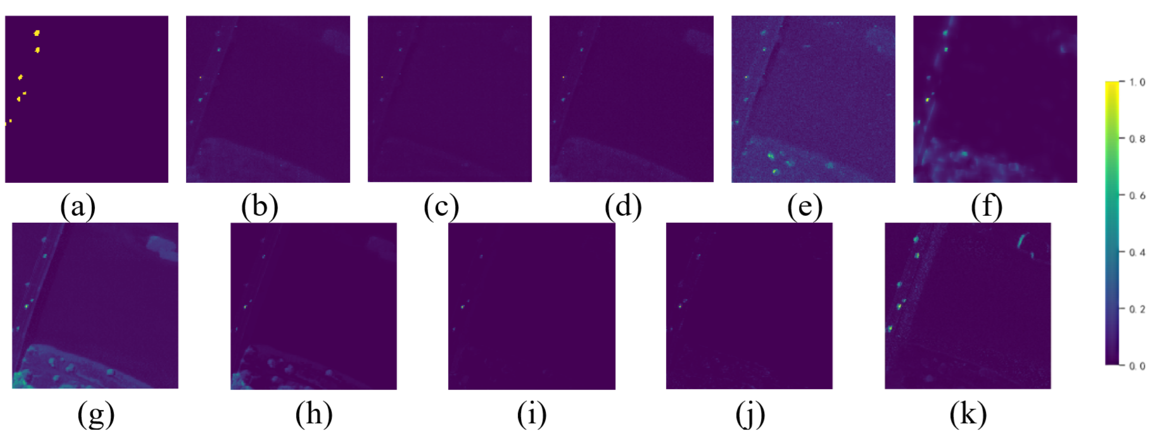

Figure 3: The heat maps of the Pavia dataset: (a) ground truth (b) GRX (c) LRX (d) FRFE (e) CRD (f) AED (g) LRASR (h) GAED (i) RGAE (j) Auto-AD and (k) ours.

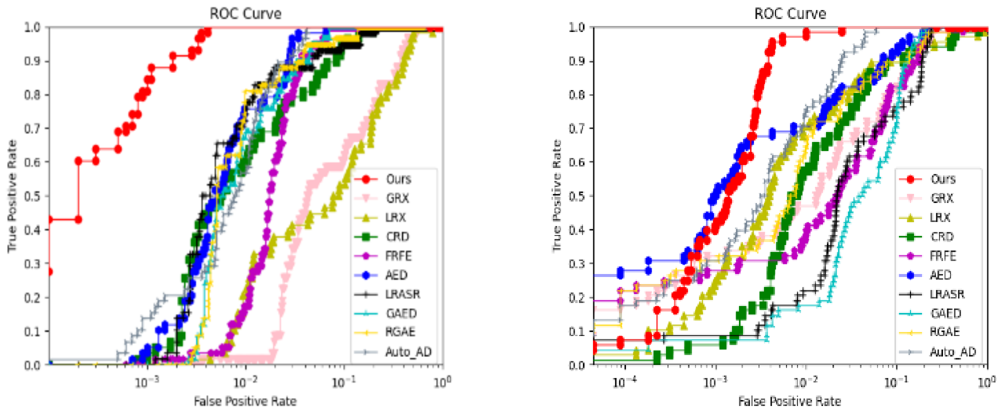

Figure 4: The ROC curves are plotted for the two selected datasets: (left) San Diego (right) Pavia.

Table 1: AUC values on various datasets

Method	**GRX**	**LRX**	**FRFE**	**CRD**	**AED**	**LRASR**	**GAED**	**RGAE**	**Auto**	**Ours**
SanDiego	0.874	0.857	0.979	0.977	0.990	0.982	0.986	0.985	0.989	0.999
Pavia	0.954	0.953	0.946	0.951	0.979	0.938	0.940	0.969	0.991	0.997

4. Conclusion

The present study introduces a novel full convolutional autoencoder, namely FCAE-HAD, for hyperspectral anomaly detection. We utilize a fully convolutional autoencoder. The detection performance demonstrates the superiority of this method over existing advanced HAD methods. The validity experiment further substantiates the dependability and practicability of the FCAE-HAD method. The limitations of our method, however, include the necessity for manual parameter adjustments, which may not sufficiently cater to its practical versatility. The focus of our future work will primarily be on the development of an adaptive approach, with the objective of achieving efficient and rapid HAD without dependence on any pre-established parameters.

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