H-042

Disaster Damage Detection from Hyperspectral Images using Discriminative Self-attention

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Abstract

Disaster damage detection is essential for effective response and recovery efforts following natural events such as earthquakes, floods, hurricanes, and wildfires. Traditional methods, while foundational, are often limited by their resource-intensive and subjective nature. This paper explores the advanced capabilities of hyperspectral imaging (HSI) in enhancing disaster damage detection. This paper proposes a novel multi-object disaster damage detection model from hyperspectral images using a discriminative self-attention module based on the proposed model to improve the accuracy.

Keywords: Damage Detection, Hyperspectral Images, Self-attention

1. Introduction

1.1 Disaster damage detection

Natural disasters, including earthquakes, hurricanes, floods, and wildfires, cause extensive damage to infrastructure, ecosystems, and human lives. The ability to quickly and accurately assess the damage following such events is crucial for effective disaster response and recovery. Traditional methods of damage detection, which often rely on manual inspections and ground-based surveys, can be slow, dangerous, and resource-intensive. These limitations highlight the need for more advanced, efficient, and accurate damage detection techniques.

In recent years, advancements in technology have revolutionized the field of disaster damage detection. Satellite imagery, drones, and ground-based sensors provide a wealth of data that can be analyzed to assess damage over large areas with greater speed and precision. Moreover, the advent of artificial intelligence (AI) and machine learning (ML) has further enhanced our ability to interpret this data, offering new possibilities for automating damage detection processes and improving their accuracy.

1.2 Hyperspectral images

Hyperspectral images capture detailed information across a wide spectrum of light, beyond what is visible to the human eye, by recording data in hundreds of narrow wavelength bands. This detailed spectral information allows for precise identification and analysis of materials, making hyperspectral imaging invaluable for applications like disaster damage detection. By detecting subtle changes in materials, such as stressed vegetation or structural damage, hyperspectral images enhance the accuracy and effectiveness of damage assessment, leading to better-informed response and recovery efforts.

2. Related Work

For disaster detection, there are some related works. Reference [1] present an unsupervised deep learning approach for post-disaster building damage detection from RGB images, reference [2] described a variety of U-Nets using different backbones with the attention mechanism which can automatically detect damaged buildings in RGB satellite images and assess their level, and [3] tested an advanced CNN for single visible structural damage detection with RGB datasets from different sensors to show what deep learning networks can currently deliver. [4] focused on earthquake building detection from UAV images and proposed that low-cost unmanned aerial vehicles or robots can be leveraged as a viable alternative for quick reconnaissance. And in [5], a novel method based on TLD framework for detecting the damaged road region from post-disaster high-resolution remote sensing RGB image is presented. There are also several work about building damage detection from RGB images of satellite or UAV[7-13]

In this paper, a new multi-object disaster damage detection network from hyperspectral images is designed and a new kind of self-attention module is proposed.

3. Proposed Method

3.1 Proposed framework of disaster damage detection based on hyperspectral classification

As mentioned above, the existing disaster damage detection work is mainly for single object detection in RGB images, that is, the detection result is a binary damage image. However, in practice, it is necessary to obtain more valuable information about the disaster area. On the other hand, hyperspectral images have broader and more detailed spectral information than RGB images and have great application prospects. Therefore, we propose to use hyperspectral images for more comprehensive disaster damage detection to obtain more information, such as changes in ground object categories, damage levels, etc.

Furthermore, considering the limitations of single-object damage detection in practice and the richness of hyperspectral information, we proposed a multi-object damage detection model based on hyperspectral classification network[14,15], which the structure of the

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model is shown in Figure 2. The basic branch is a hyperspectral classification network. The images of the two time periods before and after the disaster are classified by the same classification network to obtain category images, and then the change detection is directly performed by comparison, and finally the multi-object damage detection image is obtained. It should be noted that the pre-disaster images can be pre-stored in the database, and the requirements for the time interval are very loose, and it is only necessary to ensure that the post-disaster images are near real-time.

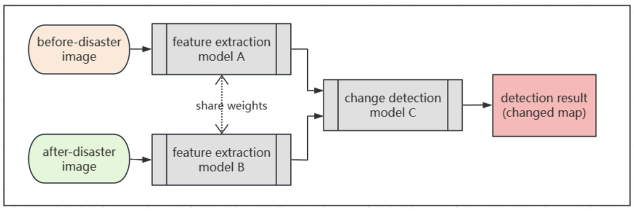

Figure 1 Existing damage detection model

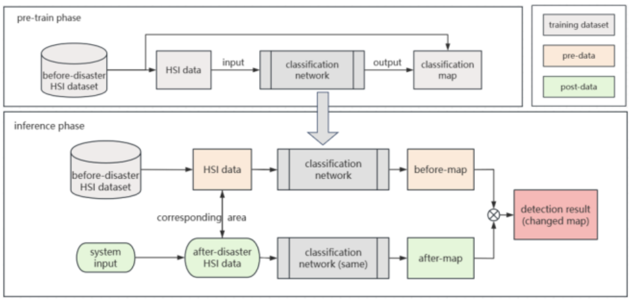

Figure 2 Proposed multi-object damage detection model based on hyperspectral classification network

In terms of training and deployment, our model is very different from existing models. Generally speaking, training a damage detection network usually requires three types of data as samples: before-image, after-image, and the ground truth of the result (usually binary map), which often encounters two major difficulties: sampling time and labeling. Our model uses the classification network as the basic branch model, so during the training phase, only samples consisting of pre-disaster images and corresponding category labels are required, which can be easily obtained and included in the pre-disaster HSI database.

3.2 Discriminative self-attention module

3.2.1 Attention

The attention mechanism is a fundamental concept in neural networks, particularly in sequence-to-sequence models used in natural language processing (NLP), computer vision, and other areas. It allows the model to focus on specific parts of the input sequence when generating each element of the output sequence, enabling the model to handle dependencies that can be far apart in the input sequence.

Assuming X is a matrix, the simplest attention formula can be expressed as:

$$\mathrm{Attention}(X) = \mathrm{softmax}(XX^T)X, \qquad (1)$$

where $\mathrm{softmax}(XX^T)$ can be considered as the weight of the matrix X itself.

3.2.2 Discriminative self-attention

We found that when using a hyperspectral classification network for multi-object damage detection models, since the previous and subsequent images share the same classification network and the network is trained with pre-disaster data, new categories that should appear in post-disaster images will be misclassified, resulting in decreased damage detection accuracy and incorrect category change information. To solve this problem, we proposed an attention module called discriminative self-attention module.

This module consists of three parts: weight calculation, calibration calculation and discriminative matrix. The input of this module is the initial hyperspectral image, and the output is the calibrated hyperspectral image and discriminative index. The weight part includes the self-attention calculation of spectral attention and local spatial attention, which the band weights and pixel weights are obtained respectively. Then, the calibrated hyperspectral image is obtained through the weights. After that, the discriminative matrix of each spatial pixel is intercepted from the calibrated hyperspectral image in turn according to the local window, and the discriminative index is calculated. Finally, the subsequent operation is performed or not according to the discriminative index and the set hyperparameter threshold.

This module can distinguish the damaged pixels in the post-image and classify them directly, while also enhancing the robustness of the overall model. In addition, this module also has the function of optimizing relatively complex hyperspectral band features.

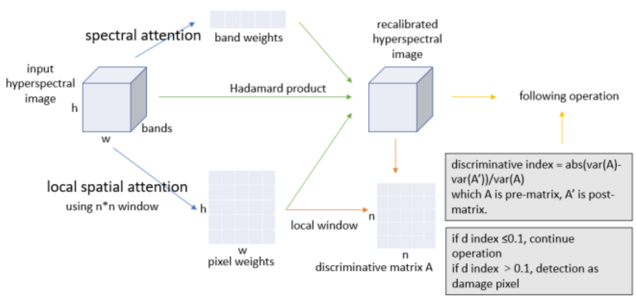

Figure 3 Discriminative self-attention module

3.3 Overall structure

In short, compared with existing models, our model has the following advantages:

The model outputs more information, allowing for faster post-disaster assessment and recovery

The model training and deployment strategy is more convenient, the model structure is simpler, and it is more suitable for dealing with complex scenarios in practice.

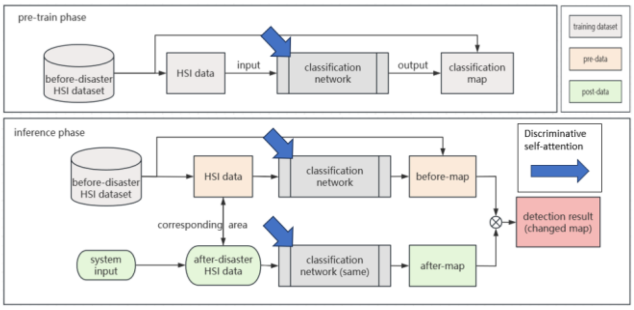

Figure 4 Overall structure of proposed model

4. **Experimental Result**

4.1 Dataset

Unfortunately, we did not find any open-source disaster damage hyperspectral dataset, so we chose to use famous hyperspectral classification datasets and hyperspectral change detection datasets instead.

4.1.1 Hyperspectral classification datasets

The first HSI was acquired by the AVIRIS sensor over the Indian Pines region in Northwestern Indiana in 1992. The image size in pixel is 145 ×145 , with a moderate spatial resolution of 20 m. The number of data channels in the acquired image is 220 (with a spectral range from 0.4 to 2.5 μm). A total of 200 radiance channels are used in the experiments by removing several noisy and water-absorbed bands.

The second HSI was acquired by the ROSIS sensor over the urban area of the University of Pavia, Italy. The image size in pixel is 610 ×340 , with a very high spatial resolution of 1.3 m. The number of data channels in the acquired image is 103 (with a spectral range from 0.43 to 0.86 μm).

The third HSI was acquired by the AVIRIS sensor over Salinas Valley in southern California, USA. The image size in pixels is 512×217 , with a spatial resolution of 3.7 m. The number of data channels in the acquired image is 224 (with a spectral range from 0.4 to 2.5 μm). A total of 204 radiance channels are used in the experiments by removing the noisy and water-absorbed bands.

	Size	Band	Class
Indian	145*145	200	16
Pavia	1096*715	102	9
Salinas	512*217	204	16

Figure 5 Classification datasets

Since the hyperspectral classification data lacks before-and-after images, we additionally use a noise generation module to generate post-disaster images and corresponding damage detection images for evaluation.

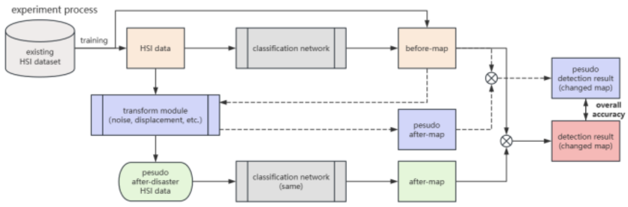

Figure 6 Flow chart for classification dataset

4.1.2 Hyperspectral change detection datasets

The Santa Barbara scene, taken on the years 2013 and 2014 with the AVIRIS sensor over the Santa Barbara region (California) whose spatial dimensions are 984*740 pixels and includes 224 spectral bands.

The Bay Area scene, taken on the years 2013 and 2015 with the AVIRIS sensor surrounding the city of Patterson (California) whose spatial dimensions are 600*500 pixels and includes 224 spectral bands.

	Santa Barbara		Bay Area	
	Absolute	Percentage	Absolute	Percentage
Changed Pixels	52134	7.16%	38425	12.81%
Unchanged Pixels	80418	11.04%	34211	11.40%
Unknown Pixels	595608	81.80%	227364	75.79%
Total	728160	100.00%	300000	100.00%

Figure 7 Change detection datasets

4.2 Experiment

The experiment was conducted on RTX3090 and python3.7. SEResNeXt and S3Net[6] were used as the baseline classification model. Post-disaster image generation used 20% Gaussian noise in the spectral domain and 10% random noise in the spatial domain. Three experiments were conducted before and after adding the attention module, and the overall average results are as follows.

	IP	Pavia	Salinas	Santa	Bay
SEResneXt (%)	57.32	48.57	52.90	65.42	70.36
SEResneXt+DSA (Ours)(%)	62.55	58.15	54.67	76.15	77.20
S3Net(%)	60.46	45.35	56.83	66.52	68.21
S3Net+DSA (Ours)(%)	62.96	51.21	57.97	71.40	75.73

Figure 8 Experimental result

It should be noted that because there is no existing result of disaster damage detection with hyperspectral dataset, so we implement the classification model as backbone and baseline for evaluation by ourselves.

4.3 Discussion

4.3.1 Applicability and Sensitivity of Discriminative Self-attention module

First, from the overall experimental results, it can be concluded that the attention module is effective, and the detection accuracy is improved after adding the module to the model. Secondly, compared with the S3Net network, our module has a stronger affinity for the SEResNeXt network that also contains an attention mechanism, and the accuracy improvement is greater. Finally, the accuracy of the simulation experiment is relatively low, which may be caused by the added noise being too random and without specific features.

4.3.2 Practicality in Real-world Operations

Hyperspectral imaging is a powerful tool for disaster damage detection, offering numerous advantages over traditional imaging techniques. By capturing a wide spectrum of light across hundreds of narrow bands, HSI provides detailed spectral information that can be used to identify and classify materials with high precision.

However, cost and accessibility is still one of the major problems in the practical application of hyperspectral technology. The acquisition of hyperspectral data typically involves expensive equipment and technology, such as specialized cameras and sensors mounted on satellites, aircraft, or drones. Ensuring accessibility and affordability of this technology is crucial for widespread adoption. Although it is not applicable at present due to data cost and accessibility reasons, we believe that with the popularization of civilian hyperspectral satellites, the detection model proposed in this paper will be realized in practice soon.

5. Conclusion

This paper proposes a novel multi-object disaster damage detection model from hyperspectral images, and proposes a discriminative self-attention module based on the proposed model architecture to improve the model and improve the accuracy. Experiments show that the proposed architecture can achieve basic functions on hyperspectral classification datasets and hyperspectral change detection datasets, and the discriminative self-attention module is absolutely effective. Compared with existing related work, our proposed method has better training and deployment strategies, can obtain more detection information, and has stronger robustness and portability. Besides, there is still room for improvement and enhancement of hyperspectral classification models and detection accuracy, and the cost and acquisition of hyperspectral data are still a big problem.

Acknowledgement

The authors declare no conflict of interest. Haoming Li: Conceptualization, Methodology, Research, Experiment, Validation. Sei-ichiro Kamata: Conceptualization, Research, Validation. I would like to express my great appreciation to my supervisor Sei-ichiro Kamata for his consecutive suggestions.

References

[1] Tilon S, Nex F, Kerle N, et al. Post-disaster building damage detection from earth observation imagery using unsupervised and transferable anomaly detecting generative adversarial networks[J]. Remote sensing, 2020, 12(24): 4193.
[2] . Wu C, Zhang F, Xia J, et al. Building damage detection using U-Net with attention mechanism from pre-and post-disaster remote sensing datasets[J]. Remote Sensing, 2021, 13(5): 905.
[3] Nex F, Duarte D, Tonolo F G, et al. Structural building damage detection with deep learning: Assessment of a state-of-the-art CNN in operational conditions[J]. Remote sensing, 2019, 11(23): 2765.
[4] Ghosh Mondal T, Jahanshahi M R, Wu R T, et al. Deep learning‐based multi‐class damage detection for autonomous post‐disaster reconnaissance[J]. Structural Control and Health Monitoring, 2020, 27(4): e2507.
[5] Zhao K, Liu J, Wang Q, et al. Road damage detection from post-disaster high-resolution remote sensing images based on tld framework[J]. IEEE Access, 2022, 10: 43552-43561.
[6] Xue Z, Zhou Y, Du P. S3Net: Spectral–spatial Siamese network for few-shot hyperspectral image classification[J]. IEEE Transactions on Geoscience and Remote Sensing, 2022, 60: 1-19.
[7] Xu J Z, Lu W, Li Z, et al. Building damage detection in satellite imagery using convolutional neural networks[J]. arXiv preprint arXiv:1910.06444, 2019.
[8] Singh R, Verma P. Damage detection caused by natural disaster using image processing technique[J]. Int. J. Recent Innov. Trends Comput. Commun, 2015, 3(4): 2287-2291.
[9] Li Y, Hu W, Dong H, et al. Building damage detection from post-event aerial imagery using single shot multibox detector[J]. Applied Sciences, 2019, 9(6): 1128.
[10] Balz T, Liao M. Building-damage detection using post-seismic high-resolution SAR satellite data[J]. International Journal of Remote Sensing, 2010, 31(13): 3369-3391.
[11] Li Y, Lin C, Li H, et al. Unsupervised domain adaptation with self-attention for post-disaster building damage detection[J]. Neurocomputing, 2020, 415: 27-39.
[12] Dong L, Shan J. A comprehensive review of earthquake-induced building damage detection with remote sensing techniques[J]. ISPRS Journal of Photogrammetry and Remote Sensing, 2013, 84: 85-99.
[13] Yamazaki F, Matsuoka M. Remote sensing technologies in post-disaster damage assessment[J]. Journal of Earthquake and Tsunami, 2007, 1(03): 193-210.
[14] He L, Li J, Liu C, et al. Recent advances on spectral–spatial hyperspectral image classification: An overview and new guidelines[J]. IEEE Transactions on Geoscience and Remote Sensing, 2017, 56(3): 1579-1597.
[15] Hennessy A, Clarke K, Lewis M. Hyperspectral classification of plants: A review of waveband selection generalisability[J]. Remote Sensing, 2020, 12(1): 113.