南京审计大学

博士生导师任职申请附件材料

申 请 人 姓 名 　　　詹天明

学科、专业名称 　　统计学/人工智能

所　在　学　院 　　　计算机学院

填　表　日　期 　　2025 年 11 月 17 日

南京审计大学研究生院制表

目 录


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中华人民共和国
居民身份证
签发机关 南京市公安局鼓楼分局
有效期限 2019.12.24-2039.12.24

博士研究生

毕 业 证 书

研究生 詹天明　　性别 男， 1984 年 10 月 7 日生，于

2009 年 9 月至 2013 年 10月在 控制科学与工程

专业学习，学制 4 年，修完博士研究生培养计划规定的全部课程，成绩合格，

毕业论文答辩通过，准予毕业。

培养单位：南京理工大学　　校(院、所)长：王晓锋

证书编号：102881201301000224　　二〇一三年 十 月 三十日

中华人民共和国教育部学历证书查询网址：http://www.chsi.com.cn

博士学位证书

詹天明，男，1984年10月7日生。在南京理工大学控制科学与工程学科（专业）已通过博士学位的课程考试和论文答辩，成绩合格。根据《中华人民共和国学位条例》的规定，授予工学博士学位。

南京理工大学　　校　长
学位评定委员会主席　王晓锋

证书编号：1028822013000224

二〇一三年十月三十日

江苏省高级专业技术资格
证书

此证表明持证人具有担任相应专业技术职务的任职资格

姓　　名：詹天明

性　　别：男

出生年月：1984-10-07

身份证号：321084198410075216

工作单位：南京审计大学

评委会名称：江苏省南京审计大学教师高级专业技术资格评审委员会

资格名称：　教授

系列（专业）：高校教师系列

专业（学科）：计算机科学与技术

证书号：　223200004091120007

取得资格时间：2022-10-29

文件号：　南审人发〔2022〕68号

在线证书信息

南京审计大学
职称专用章

盖签发单位电子印章

证 书

经研究，确定 詹天明 同志为江苏省高层次人才培养计划（“333工程”）第七期第二层次培养对象，培养管理期从2024年11月至2029年10月。

中共江苏省委人才工作领导小组办公室　　江 苏 省 教 育 厅

二〇二四年十一月

证书编号：（2024） 2-079 号

江 苏 省 教 育 厅

苏教师函〔2021〕11 号

省教育厅关于公布 2021 年
江苏高校“青蓝工程”培养对象的通知

各有关高校:

根据《省教育厅关于开展 2021 年高校“青蓝工程”培养对象选拔工作的通知》要求，经学校推荐、专家评审、人选公示等程序，现将 2021 年高校“青蓝工程”优秀青年骨干教师 500 人、中青年学术带头人 200 人、优秀教学团队 100 个的名单予以公布(具体名单见附件 1-3）。现就有关事项通知如下。

一、培养要求

各类培养对象的培养期为 2021 年 6 月至 2024 年 6 月。有关高校要按照《江苏高校“青蓝工程”管理办法》（苏教规〔2017〕2 号），认真做好培养对象的培养工作，明确学校、院系和培养对象各自的职责，采取切实措施，重点抓好培养、管理和考核等环节。

二、经费支持

每位优秀青年骨干教师资助科研经费 4 万元，自然科学类、人文社会科学类中青年学术带头人分别资助科研经费 10 万元、8 万元，每个优秀教学团队资助科研经费 30 万元，以上经费由省教育厅和所在学校各承担 50%。资助经费主要用于开展科研和教学项目研究、参加学术会议和培训进修、出版学术专著等，不得用于发放生活津贴。所在学校应严格执行有关财务管理规定，对资助经费单独建帐，专款专用。培养对象在“青蓝工程”资助下取得的成果，包括发表论著和成果鉴定等，须标注“江苏高校‘青蓝工程’资助” 字样。

三、培养计划

各校要组织培养对象研究制订 3 年培养计划，认真填写《2021 年江苏高校“青蓝工程”培养对象目标责任书》（附件 4），于 2021 年 6 月 30 日前将目标责任书报省教育厅教师工作处。联系人：李辉，电话：025-83335120、83335619，邮箱：nj86788@163.com。

附件：1. 2021 年江苏高校“青蓝工程”优秀青年骨干教师培养对象名单
2. 2021 年江苏高校“青蓝工程”中青年学术带头人培养对象名单
3. 2021 年江苏高校“青蓝工程”优秀教学团队名单
4. 2021 年江苏高校“青蓝工程”培养对象目标责任书

省教育厅

2021 年 5 月 14 日

（此件主动公开）

附件 1

2021 年江苏高校“青蓝工程”优秀青年骨干教师名单

（共 500 人）

南京大学（4 人）

韩玉胜、温权、王成、夏天娇

东南大学（6 人）

谈超群、丁溢、陈良斌、陈文雪、莫凌飞、刘艾然

南京航空航天大学（6 人）

谢文忠、魏佳丹、张劲东、张镜洋、王艳军、姜金辉

南京理工大学（5 人）

郑侃、钱建军、程诚、彭勇、刘佳

河海大学（6 人）

俞晓东、刘建超、江善虎、邵智斌、应国兵、许楠

南京农业大学（6 人）

袁军、肖燕、吴梅笙、邱威、蓝菁、李昕升

中国药科大学（5 人）

徐晓莉、卞金磊、陈松、郑啸、徐澍

南京森林警察学院（4 人）

张帆、马艳君、吴育宝、邱明月

江南大学（6 人）

刘勇、李会、廖红梅、王宁、吴郁、刘佳

中国矿业大学（5 人）

江帆、代伟、康建宏、李伍、汪超

南京师范大学（5 人）

王彦强、徐芹、章乐、翁山杉、万密密

南京工业大学（5 人）

王静虹、杨世品、庄雷、任鑫、蒋博雅

南京信息工程大学（5 人）

田青、程中华、王壮、郑柏超、李志强

南京邮电大学（6 人）

王鸿、金久仁、周剑、王正新、宋春元、李文梅

南京林业大学（6 人）

孙海军、王新洲、黄曹兴、陈动、李亚平、陈斌

南京医科大学（5 人）

张汝阳、徐志鹏、张丽颖、朱猛、王华

南京中医药大学（6 人）

季德、葛菲菲、杨涛、江星、陈勇、纪建建

南京艺术学院（4 人）

霍春晓、韩栩、杜卉、邢璐

南京财经大学（5 人）

谭文浩、沈飞、查利娟、张正勇、刘凯

南京审计大学（6 人）

徐宁、李姗姗、王静、徐彰、王江艳、詹天明

证 书

詹天明 同志入选2021年江苏省科技副总项目。

（编号：FZ20210198　合作企业：南京智莲森信息技术有限公司　派出单位：南京审计大学）

江苏省人才工作领导小组办公室　江苏省科学技术厅

二〇二一年八月

第十三届中国大学生服务外包创新创业大赛

企业命题类

一等奖

参赛院校

南京审计大学

参赛学生

孙艳文	南京审计大学
徐　辉	南京审计大学
袁梦雪	南京审计大学
张煜茜	南京审计大学
祁家强	南京审计大学

指导老师

詹天明	南京审计大学
万鸣华	南京审计大学

中国大学生服务外包创新创业大赛组委会

二〇二二年八月

荣誉证书

HONORARY CREDENTIAL

詹天明同志被选为珠海市审计学会第六届理事会副会长。

珠海市审计学会

2021年12月

Spatial–Spectral Feature-Enhanced Mamba and SAM-Guided Hyperspectral Multiclass Change Detection

Tianming Zhan, Jiaqiang Qi, Jinjin Zhang, Xiaobin Yu, Qian Du, *Fellow, IEEE*, and Zebin Wu, *Senior Member, IEEE*

***Abstract*—Multiclass change detection from hyperspectral image (HSI) leverages the rich spectral information of HSIs to detect and classify subtle changes in interest in an imaged scene. However, challenges arise due to limited samples in small categories, which hinder the accurate differentiation of changes. This study proposes a spatial–spectral feature-enhanced Mamba and SAM-guided (SFMS) hyperspectral multiclass change detection method. To address the challenges, a tri-plane gated Mamba (tri-Mamba) is designed to complement spatial information using the abundant spectral information in HSIs. In addition, frequency-domain features are combined with state-space models, enabling the detection of more accurate semantic and texture changes using integrated information from frequency domains. This approach effectively mitigates the problem of inaccurate detection in small-sample categories. Furthermore, the segment anything model (SAM) is adapted, with the features of change areas being enhanced through prior knowledge obtained from segmentation, thereby improving the multiclass change detection accuracy. The experimental results demonstrate that the proposed SFMS method outperforms state-of-the-art techniques, achieving superior multiclass change detection while overcoming the challenges associated with detecting small-sample categories.**

***Index Terms*—Mamba, multiclass change detection, segment anything, wavelet.**

I. INTRODUCTION

CHANGE detection has long been a significant area of research in computer vision, which focuses on identifying alterations in the same region over different time phases. With the rapid development of remote sensing technology, hyperspectral image (HSI) has gained increasing prominence due to its high spectral resolution. Key study areas related to HSI include target detection [1], [2], [3], classification [4], [5], [6], image fusion [7], [8], [9], and change detection [10], [11], [12]. Among these, HSI change detection remains among the most widely studied and impactful topics. These methods are commonly used to monitor the evolution of natural environmental features [13], [14], as well as for disaster assessment and early warning systems [15]. HSI change detection methods can be binary and multiclass. While binary change detection provides useful information, it is often insufficient for specialized tasks. In contrast, multiclass change detection allows identifying a broader range of changes, through using richer and more detailed information.

HSI change detection can be achieved using three main approaches: traditional algebra-based methods, classical machine learning techniques, and deep learning methods. Early change detection methods primarily relied on algebraic computations, such as change vector analysis (CVA) [16], which identifies changes by calculating the spectral vector difference between images from two phases. However, this method requires selecting an appropriate threshold and often involves complex image preprocessing steps. While traditional methods offer advantages in spectral information processing, they are highly sensitive to environmental variations and noise, resulting in poor performance in complex or dynamic scenes.

Classical machine learning approaches can address the limitations of traditional methods. These augmented methods handle the challenges posed by environmental noise and variations more effectively due to their ability to automate and systematize feature extraction. For example, support vector machines (SVMs) [17] have been widely used in hyperspectral change detection due to their strong generalization capability in high-dimensional spaces and their effectiveness in separating changed and unchanged classes. SVMs construct optimal hyperplanes to distinguish between classes, even in cases where the spectral distributions are complex and nonlinear. In the context of HSI, where redundant and noisy spectral bands are common, SVM-based methods have shown superior performance in maintaining detection accuracy under varying imaging conditions.

Despite these advances, classical machine learning techniques often require manual feature extraction, which, while capable of improving detection performance, depends heavily

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Digital Object Identifier 10.1109/TGRS.2025.3581935

A Novel Cross-Scale Octave Network for Hyperspectral and Multispectral Image Fusion

Tianming Zhan, Zuolin Bi, Huapeng Wu, Chao Xu, Qian Du, *Fellow, IEEE*, Yang Xu, *Member, IEEE*, and Zebin Wu, *Senior Member, IEEE*

***Abstract*—Recently, deep convolutional neural network-based low-resolution hyperspectral image (LR-HSI) and high-resolution multispectral image (HR-MSI) fusion methods have achieved significant performance improvement. However, the rich spatial and spectral information in HSIs is not fully explored. In this article, we propose a novel cross-scale octave network (CSONet) for hyperspectral and multispectral image fusion. Specifically, we adopt a progressive image fusion structure to effectively extract the spatial and spectral information of HR-MSI at multiple resolutions, thereby efficiently complementing LR-HSI's information. In addition, the proposed cross-scale octave convolution module can extract rich multiscale spatial feature information and concentrate on more important spatial–spectral features at different scales with the multiscale spatial–spectral attention mechanism. Finally, a multisupervised loss function is used to improve the gradient propagation and enhance the representation ability of the network. Ablation analysis on the benchmark datasets shows the effectiveness of each component in the proposed method. Extensive experimental results on different hyperspectral images demonstrate that the proposed CSONet can achieve superior results and strong generalization ability in comparison with some state-of-the-art LR-HSI and HR-MSI fusion methods.**

***Index Terms*—Attention mechanism, convolutional neural network (CNN), cross-scale octave convolution, hyperspectral and multispectral image fusion.**

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Digital Object Identifier 10.1109/TGRS.2022.3229086

I. Introduction

Hyperspectral images have been widely used in many different fields because of their rich spatial and spectral information, such as target recognition [1], classification [2], and land exploration [3]. However, due to physical limitations, the information provided by a single sensor is incomplete. The resolution of remote sensing images obtained from a single sensor can only be a compromise between spatial and spectral resolution [4]. For example, low-resolution hyperspectral images (LR-HSIs) usually have a high spectral resolution, but their spatial resolution is coarse; high-resolution multispectral images (HR-MSIs) have a higher spatial resolution, but the spectral resolution is relatively low. Therefore, how to obtain a hyperspectral image with the high spatial resolution has become an interesting research topic. Hyperspectral and multispectral image fusion is an important approach to improve the spatial resolution of the observed LR-HSI. The objective of hyperspectral and multispectral image fusion is to integrate the fine spatial texture information contained in HR-MSI and the rich spectral information contained in LR-HSI to obtain a fused image with high spatial and spectral resolution. With the increasing demand for high-resolution remote sensing data, many remote sensing image fusion methods (including pan-sharpening and HSI super-resolution) have been proposed in recent years, such as component substitution (CS)-based methods [5], [6], multiresolution analysis (MRA)-based methods [7], model-based approaches [8], and deep learning-based methods [9].

In the CS-based methods, spectral conversion is performed on the MS image so that one or all of the components are replaced by the PAN image to match the histogram. Commonly used methods based on component replacement include the intensity-hue-saturation (IHS) method [10] and the principal component analysis (PCA) method [11]. The advantage of this method is that the geometric structure is well preserved, thereby obtaining an output image with fine spatial details. On the other hand, the component replacement-based methods carry additional spectral information and cause spectral distortion. The methods based on MRA are expected to infer the missing spatial details of MS images from PAN images and inject them into MS images. In order to improve the effectiveness of the detail injection, wavelet-based methods are proposed to perform image fusion. The model-based method reconstructs the hyperspectral images with high spatial

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REGULAR PAPER

A novel gradient and semantic-aware transformer network for low-light image enhancement

Tianming Zhan[1,2] · Chenyang Lu[1] · Huapeng Wu[1] · Chenyun Wang[1]

Received: 28 September 2024 / Accepted: 3 February 2025

Abstract
The advent of deep learning has significantly propelled the advancement of low-light image enhancement techniques, yielding promising experimental outcomes. However, a series of image degradation problems such as noise and texture details have not been effectively handled, leaving room for further improvement of low-light image enhancement performance. In this work, we introduce a novel framework, the gradient and semantic-aware transformer network (GSTN), specifically tailored for low-light image enhancement. Our model comprises three pivotal components: the pre-lighten network (PLNet), which serves to light up the image to present more details and extract the illumination feature; the prior-guided enhancement module, designed to restore image details and mitigate noise leveraging the original gradient features; and the illuminance adjustment module (IAM), which refines the illumination of the enhanced image. In addition, we introduce discrete wavelet transform to implement cross-domain feature interactions and multi-scale feature fusion. Extensive experiments show that that our methods obtains better results in comparison with some state-of-the-art low-light image enhancement methods on different low-light datasets.

Keywords Low-light image · Transformer · Discrete wavelet transform · Multi-scales

1 Introduction

Images captured in low-light environments are frequently marred by exposure anomalies, noise interference, and poor contrast, which significantly degrade visual aesthetics. More critically, these imperfections can severely impede subsequent computational tasks, including object detection and image segmentation. Addressing these issues, low-light image enhancement has emerged as an essential pre-processing step, aiming to brighten the image, elucidate details in dark areas, and suppress noise [1, 2].

In the past few years, many approaches have been proposed in the field of low-light enhancement which are mainly classified into traditional-based and learning-based methods. We summarise the differences between the two in Table 1. The traditional methods, which form the foundation of this field, primarily involve histogram equalization, gamma correction, and retinex-based techniques. Histogram equalization [3–5] enhances images by leveraging their statistical properties, effectively broadening the dynamic range of pixel values to augment contrast. Gamma correction [6–8], on the other hand, amplifies the contrast by adjusting the ratio between the darker and lighter regions of the image signal. Methods based on retinex theory [9–14] typically involve decomposing the image into reflective and illuminative components, with the most straightforward approaches utilizing the derived reflective component as the final enhanced output.

Communicated by Teng Li.

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Published online: 14 March 2025

TDSSC: A Three-Directions Spectral–Spatial Convolution Neural Network for Hyperspectral Image Change Detection

Tianming Zhan, Bo Song, Le Sun, Xiuping Jia, *Senior Member, IEEE*, Minghua Wan, Guowei Yang, and Zebin Wu, *Senior Member, IEEE*

***Abstract*—Change detection (CD) is a hot issue in the research of remote sensing technology. Hyperspectral images (HSIs) greatly promote the development of CD technology because of their high resolution in the spectral domain. However, some traditional CD methods currently applied to low-dimensional and multispectral images cannot adapt to the complex high-dimensional features of the HSIs. In addition, the spectral measurements of the HSI contain a lot of noise and redundancy, which greatly contaminates spectral-only information for CD. In order to fully extract the discriminant features of HSI to improve the accuracy of CD, this article proposes a three-directions spectral–spatial convolution neural network (TDSSC). A novel method for three-direction decomposition of hyperspectral change tensors is proposed—change tensor is decomposed along the spectral direction and two spatial directions to get a single tensor containing the spectral information and two kinds of tensors containing the spectral–spatial information. TDSSC uses 1-D convolution to extract spectral features from the spectral direction as well as reducing the tensor dimension, which helps the latter network to be lightweight and significantly improves the speed of change detection. Also, it uses 2-D convolution to extract spectral–spatial features from two spatial directions of the reduced tensor, and to extract features from different directions to improve the accuracy and Kappa value of CD. The experimental results of three real hyperspectral datasets show that TDSSC is superior to most existing CD methods.**

***Index Terms*—Change detection (CD), hyperspectral image (HSI), spectral–spatial combination, three directions convolution neural network.**

I. Introduction

REMOTE sensing satellite hyperspectral image (HSI) is a dataset that contains spatial information and abundant spectral information. It has become an important data source for object observation because it contains more spectral information than multispectral images (MSI). Change detection (CD) using multiperiod remote sensing satellite image technology has important application value in land cover analysis [1], ecosystem monitoring [2], portraying urban change [3], and so forth. The task of remote sensing image CD includes the following—to judge whether changes have occurred, to determine where changes have occurred, and to identify the types of changes. These tasks and their combinations correspond to commonly used CD types for remote sensing images [4]—anomaly CD [5]–[9], binary CD [10]–[15], multiclass CD [16], [17], and time-series CD [18], [19].

The CD of remote sensing images can generally be divided into four steps [20]—data acquisition, data preprocessing, change detection, and results output. The algorithm of CD is the core of determining the CD result. In the problem of single-band and multispectral CD, many researchers have proposed a variety of detection algorithms, such as change vector analysis, principal component analysis, iterative multivariate change detection, and so on. The main starting point of these methods is to extract the characteristics of spectral change vectors by algebraic operation, image transformation, and statistical analysis. In low-dimensional space, these methods have achieved high accuracy. However, the MSI CD algorithm for low-dimensional space is not ideal for high-dimensional HSI CD tasks [21], [22]. In addition, due to the high resolution of HSI, the spectral information of the two adjacent bands is usually highly correlated [4], which inevitably results in data redundancy. Therefore, how to analyze and process HSI data and extract useful information from a large amount of redundant data has become an important topic in the study of HSI CD.

In order to solve the problem of high-dimensional space and the large amount of data redundancy, deep learning has become

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MDPI

Article

SSCNN-S: A Spectral-Spatial Convolution Neural Network with Siamese Architecture for Change Detection

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Abstract: In this paper, a spectral-spatial convolution neural network with Siamese architecture (SSCNN-S) for hyperspectral image (HSI) change detection (CD) is proposed. First, tensors are extracted in two HSIs recorded at different time points separately and tensor pairs are constructed. The tensor pairs are then incorporated into the spectral-spatial network to obtain two spectral-spatial vectors. Thereafter, the Euclidean distances of the two spectral-spatial vectors are calculated to represent the similarity of the tensor pairs. We use a Siamese network based on contrastive loss to train and optimize the network so that the Euclidean distance output by the network describes the similarity of tensor pairs as accurately as possible. Finally, the values obtained by inputting all tensor pairs into the trained model are used to judge whether a pixel belongs to the change area. SSCNN-S aims to transform the problem of HSI CD into a problem of similarity measurement for tensor pairs by introducing the Siamese network. The network used to extract tensor features in SSCNN-S combines spectral and spatial information to reduce the impact of noise on CD. Additionally, a useful four-test scoring method is proposed to improve the experimental efficiency instead of taking the mean value from multiple measurements. Experiments on real data sets have demonstrated the validity of the SSCNN-S method.

Keywords: spectral-spatial combination; hyperspectral image (HSI); change detection (CD); Siamese network

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1. Introduction

Due to the development of remote sensing technology it is possible to obtain hyperspectral images (HSIs) of the same area at different time points. Change detection (CD) using multitemporal remote sensing data has an important application value in disaster assessment [1], terrain change analysis [2], urban change analysis [3] and resource auditing. The rich spectral and spatial information of HSIs, which contain hundreds of bands, provides a more powerful data source for object observation. In [4], the author divides CD into the following categories: anomaly detection [5–7], binary and multiclass CD [8–11] and CD based on time series data [12,13].

Many researchers have studied the multispectral CD task with a low number of bands and proposed a few CD algorithms. Change vector analysis (CVA) [14] is often combined with other methods. By calculating the spectral change vector corresponding to a pixel, the magnitude and angle of the spectral change of the pixel are analyzed. Multivariate alteration detection (MAD) [15] and iteratively reweighted multivariate alteration detection (IR-MAD) [16] are based on canonical correlation analysis (CCA) [17]. The change area is determined by calculating the values and their weights of MAD variables. In addition, it is

Tensor Regression and Image Fusion-Based Change Detection Using Hyperspectral and Multispectral Images

Tianming Zhan, Yanwen Sun, Yongsheng Tang, Yang Xu, and Zebin Wu, *Senior Member, IEEE*

***Abstract*—Change detection is a popular topic in remote sensing that is generally constrained to two remote sensing images captured at two different times. However, the optimal type of remote sensing image for change detection tasks has not yet been determined. The use of only hyperspectral images (HSIs) with low spatial resolution or multispectral images (MSIs) with low spectral resolution cannot obtain satisfactory change detection results. In this article, we propose the fusion of simultaneously captured low spatial resolution HSIs and low spectral resolution MSIs with the use of a tensor regression-based method to detect change regions from the fused images at two different time points. In this method, nonlocal couple tensor CP decomposition is initially applied to fuse the HSIs and MSIs. A difference image is then obtained by subtracting the fused images at two different time points. Thereafter, the tensors are extracted from the difference image and the tensor regression-based method is used to classify the difference image and detect the final change results. Experimental results from three real datasets suggest that the proposed method substantially outperforms the existing state-of-the-art change detection methods as well as any change detection methods using single-source images.**

***Index Terms*—Change detection, hyperspectral images (HSIs), image fusion, multispectral images (MSIs), tensor regression.**

I. Introduction

CHANGE detection refers to calculating the difference between images captured in the same area at different time points via image processing and mathematical modeling techniques [1]–[5]. Change detection based on remote sensing images is a multidisciplinary technology involving geographic science, statistical science, and computer science and represents a popular research topic in the field of remote sensing [6]–[16]. Although remote sensing image change detection methods have been widely studied, several challenges remain, such as remote sensing images containing noise, blur, and other degradation problems due to the various structures of ground features, atmospheric radiation, and other factors. Beside this, spectral variability also make it difficult for spectral unmixing or object detection [17]. Thus, relying solely on spectral information is not sufficient to distinguish different objects [18]–[20]. Spectral-spatial fusion based methods are wildly used in hyperspectral image (HSI) processing field [21]–[23]. For example, Hong *et al.* [24] proposed a novel linearized subspace analysis technique with spatial-spectral manifold alignment for hyperspectral dimensionality reduction, and overcome the drawbacks in explainability, cost effectiveness, generalization capability, and representability of conventional nonlinear subspace learning.

At present, HSIs and multispectral images (MSIs) are often used for change detection. However, using only HSIs with low spatial resolution or MSIs with low spectral resolution cannot obtain satisfactory change detection results. Additionally, the remote sensing images collected during different periods may be captured by different sensing devices, and their spatial and spectral resolutions may be inconsistent [25]. To accurately detect change areas in remote sensing images, it is very important to fuse remote sensing images from different periods to achieve the same spatial and temporal resolutions [26]–[27].

In recent years, fusing HSIs and MSIs to improve resolution has attracted much attention. The most popular fusion methods include fusion algorithms based on component replacement [28], detail injection methods [29], spectral unmixing methods [30], deep learning methods [31]–[33], and tensor representation-based methods [34]–[36]. The main idea behind the tensor representation-based fusion method involves treating high-dimensional remote sensing images as a high-order tensor and using tensor decomposition technology and a regularization method to achieve high-dimensional image fusion. Li *et al.* [37] proposed a new HSI fusion method based on non-local sparse tensor decomposition. This method initially gathers similar hyperspectral blocks into a cluster, with similar blocks sharing the same dictionary. Each cluster learns a spectral dictionary

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BRCN-ERN: A Bidirectional Reconstruction Coding Network and Enhanced Residual Network for Hyperspectral Change Detection

Bo Song, Yongsheng Tang, Tianming Zhan, and Zebin Wu, *Senior Member, IEEE*

***Abstract*— Change detection (CD) is a hot issue in the field of remote sensing. Hyperspectral images (HSIs) contain rich spectral information and have gradually become an important data source in CD. Spectral–spatial combination is a commonly used strategy for suppressing the influence of noise on the spectrum. However, it is difficult to find a feature space that allows both spectral and spatial features to be optimally expressed. Therefore, this letter proposes a bidirectional reconstruction coding network and enhanced residual network for HSI CD (i.e., BRCN-ERN) based on the strategy of completely extracting spectral and spatial features separately and then fusing them together. In the spectral module, we use the spectrum of unchanged pixels at two time points to construct a bidirectional reconstruction network, and use the reconstruction error as a new source of spectral features. In the spatial module, we use advanced band selection algorithms to filter the bands with good spatial information and design an enhanced 2-D residual network to extract the spatial features of the change tensor. Finally, the obtained spectral and spatial feature vectors are fused and inputted into the fully connected classification network to obtain the final CD map. Real HSI experiments show that our proposed BRCN-ERN has a better CD effect and is more effective than most existing algorithms.**

***Index Terms*—Bidirectional reconstruction coding network (BRCN), change detection (CD), enhanced residual network (ERN), hyperspectral image (HSI), spectral–spatial combination.**

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I. Introduction

WITH the development of remote sensing technology, change detection (CD) based on remote sensing image has important applications in urban development [1], terrain analysis [2], resource analysis [3], and other fields. Hyperspectral imaging technology is a product of the development of remote sensing technology and is also an important data source for remote sensing images. The rich spectral information of hyperspectral images (HSIs) provides more refined spectral features than traditional multispectral images. Simultaneously, it brings high dimensions and a great deal of redundancy, which introduces challenges to the feature extraction task.

Deep learning can be used for both feature extraction and data dimensionality reduction, which can effectively deal with the challenges brought by HSI. Boulch *et al.* [4] used a 1-D convolutional neural network (1DCNN) to extract rich spectral information. However, Li *et al.* [5] mentioned that only using spectral information will be limited by noise and redundancy in the spectrum. The spatial context information has been verified that it is useful for improving the performance of land-cover change detection (LCCD) with HSIs [6]. Therefore, the spectral–spatial combination strategy of integrating spectral and spatial information into feature extraction has become an important research direction. Notably, Ben Hamida *et al.* [7] and Luo *et al.* [8] used a 3-D convolutional neural network (3DCNN) that can extract spectral and spatial features simultaneously and achieved good results. However, an important fact is that it is difficult to find a feature space that allows both spectral and spatial features to be optimally expressed. No matter which feature is the main feature, the other feature will be lacking or redundant. In this context, the method proposed in this letter attempts to completely separate spectral feature extraction from spatial feature extraction before performing feature fusion.

The spectral change vector [9] is an important source of spectral change features. However, since it is affected by factors such as noise, the spectrum of the unchanged pixels at two time points will have a certain difference. Inspired by the coding network in image reconstruction, we attempt to use the spectrum of unchanged pixels at two time points for bidirectional reconstruction, and use the reconstructed error as a supplementary source of spectral features.

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ORIGINAL RESEARCH

A hybrid U-shaped and transformer network for change detection in high-resolution remote sensing images

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Abstract

Deep convolutional neural networks based remote sensing change detection has recently shown significant performance improvement. However, small region changes and global-local features in high-resolution remote sensing images are not fully explored. This paper introduces a hybrid U-shaped and transformer network for change detection in high-resolution remote sensing images. Specifically, a UNet++-based backbone to facilitate feature learning across different scales. In addition, we introduce a transformer-based feature fusion module for extracting long-range dependencies, which can enhance the representation ability of the network. Furthermore, the introduced efficient channel attention mechanism can efficiently calibrate the feature representation and concentrate on more important feature information. Thanks to the above designs, the proposed method enjoys a strong ability to extract local and global features for remote sensing change detection. Extensive experimental results on different remote sensing images show that our method can achieve superior performance in comparison with state-of-the-art change detection methods.

1 | INTRODUCTION

With the advancement and application of remote sensing technology [1], an increasing amount of data is being collected by remote sensing platforms, which are widely used in various fields. Remote sensing image CD targets the differences between the objects at different times [2], which has been an important tool for urban expansion [3–6], land exploration [7, 8], disaster assessment [9–12], and environmental monitoring [13–17]. Many factors contribute to these "semantic changes," including deformation, relative movement, addition, or disappearance of elements. The challenge of CD is to ensure that the final change map does not contain "non-semantic changes," such as camera movement, sensor noise, or lighting variations.

Deep learning has become the primary method for CD in remote sensing images due to its strong learning ability [18]. Fu et al. [19] first introduced a Siamese convolutional network for change detection (CD) tasks. Bi-temporal images can be processed simultaneously by the Siamese network structure. In ref. [20], two bi-temporal images are concatenated as the input of FC-EF. FC-Siam-conc and FC-Siam-diff use the Siamese structure to directly process the bi-temporal images. By incorporating the explicit comparison mechanism, the detection ability of FC-Siam-diff can be further improved. To expand the receptive field of the network, Zhang et al. [21] introduce dilated convolutions.

Xu et al. [21] introduce dilated convolutions to expand the receptive field of the network, which can obtain better experimental performance without adding parameters. In refs. [22, 23], they use the deep convolutional network based on ResNet18 and ResNet50, respectively, to expand the receptive field of the network, which exhibits superior detection performance in comparison with shallow networks. Fang et al. [24] propose a CD method that uses dense connections, which can effectively facilitate the flow of feature information in different layers. In refs. [25, 26], they propose CD networks based on the attention mechanism. These models can improve network's change detection performance by selectively focusing on important features with the help of attention mechanism. Although

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REGULAR PAPER

A novel spatial and spectral transformer network for hyperspectral image super-resolution

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Abstract

Recently, transformer networks based on hyperspectral image super-resolution have achieved significant performance in comparison with most convolution neural networks. However, this is still an open problem of how to efficiently design a lightweight transformer structure to extract long-range spatial and spectral information from hyperspectral images. This paper proposes a novel spatial and spectral transformer network (SSTN) for hyperspectral image super-resolution. Specifically, the proposed transformer framework mainly consists of multiple consecutive alternating global attention layers and regional attention layers. In the global attention layer, a spatial and spectral self-attention module with less complexity is introduced to learn spatial and spectral global interaction, which can enhance the representation ability of the network. In addition, the proposed regional attention layer can extract regional feature information by using a window self-attention based on zero-padding strategy. This alternating architecture can adaptively learn regional and global feature information of hyperspectral images. Extensive experimental results demonstrate that the proposed method can achieve superior performance in comparison with the state-of-the-art hyperspectral image super-resolution methods.

Keywords Hyperspectral image (HSI) super-resolution · Transformer · Window attention

1 Introduction

Hyperspectral image (HSI) is a continuous and narrow band image data with high spectral resolution, which is widely applied in various fields such as medical diagnosis [1–3], food quality and safety control [4, 5], remote sensing [6–9], object detection [10–13], and classification [14–17]. However, due to the limitations of imaging technology and hardware, the resolution of the captured hyperspectral images usually needs to be higher, which greatly limits their applications. Therefore, this is an important challenge how to obtain a high-resolution hyperspectral image.

Image super-resolution is a technology that can generate high-resolution images from low-resolution images without hardware modifications. Hyperspectral image super-resolution techniques can be divided into two categories based on the number of input images: fusion-based hyperspectral image super-resolution and single hyperspectral image super-resolution [18]. The former improves the resolution of hyperspectral image by fusing low-resolution hyperspectral image (LR-HSI) with high spatial resolution auxiliary image. However, this approach assumes that the input images have a good correlation, which is difficult to obtain in practice.

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KANformer: Dual-Priors-Guided Low-Light Enhancement via KAN and Transformer

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Images captured under low-light conditions suffer from poor visibility and clarity due to insufficient light. The emergence of deep learning has greatly boosted the development of low-light enhancement techniques and achieved promising results. However, while these low-light enhancement methods have enhanced the perceptual effects of human vision, their results in high-level visual tasks (e.g., object detection and semantic segmentation) are still unstable and even sometimes bring negative effects. Therefore, in this work, we propose a new model, KANformer, which uses a semantic-gradient prior as a guide to recover pixels relevant to the image subject from both high-frequency and low-frequency perspectives. Specifically, our model consists of three key components: Low-Frequency Enhancement (LFE) module, which aims to enhance the restoration of the image subject via the semantic prior obtained from SAM; Low-Frequency-Based High-Frequency Enhancement (LFHE) module, which utilizes the KAN module to obtain information from the low-frequency features conducive to the enhancement of high-frequency features; and Gradient-Based High-Frequency Enhancement (GHE) module, which aims to utilize the original gradient as prior to further enhance the structural information of the image and reduce the effect of noise. In addition, we introduce the discrete wavelet transform as down-sampling method while transforming the spatial domain features to the frequency domain for processing. Experiments on multiple paired and unpaired datasets show that our method achieves better visualization and image fidelity compared to other state-of-the-art methods. In addition, experiments on object detection and segmentation show that our method provides better enhancement in improving low-light high-level vision tasks.

CCS Concepts: • **Computing methodologies → Computer vision**; **Neural networks**;

Additional Key Words and Phrases: Low-light enhancement, transformer, kolmogorov-arnold networks, wavelet transform

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发明专利证书

发 明 名 称：一种具有多尺度特征融合功能的遥感影像变化检测方法

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发明专利证书

发 明 名 称：一种基于双向重建编码网络和强化残差网络的高光谱变化检测方法

发 明 人：詹天明;徐超;宋博;吴泽彬

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2023年04月07日

第 1 页 (共 2 页)

其他事项参见续页

证书号第6670320号

发明专利证书

发 明 名 称：一种基于Transformer与CNN分组融合的高光谱图像超分辨方法

发　明　人：詹天明;徐辉;徐超;徐洋;吴泽彬

专　利　号：ZL 2023 1 0381242.9

专利申请日：2023年04月11日

专 利 权 人：南京审计大学

地　　　址：210000 江苏省南京市雨山西路86号

授权公告日：2024年02月02日　　　　授权公告号：CN 116452420 B

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2024年02月02日

第1页（共2页）

其他事项参见续页

国家自然科学基金资助项目批准通知

（预算制项目）

詹天明　先生/女士：

根据《国家自然科学基金条例》、相关项目管理办法规定和专家评审意见，国家自然科学基金委员会（以下简称自然科学基金委）决定资助您申请的项目。项目批准号：62375133，项目名称：非现场审计开放环境下高光谱成像语义级变化检测方法，直接费用：48.00万元，项目起止年月：2024年01月至 2027年 12月，有关项目的评审意见及修改意见附后。

请您尽快登录科学基金网络信息系统（https://grants.nsfc.gov.cn），**认真阅读《国家自然科学基金资助项目计划书填报说明》并按要求填写《国家自然科学基金资助项目计划书》（以下简称计划书）**。对于有修改意见的项目，请您按修改意见及时调整计划书相关内容；如您对修改意见有异议，须在电子版计划书报送截止日期前向相关科学处提出。

请您将电子版计划书通过科学基金网络信息系统（https://grants.nsfc.gov.cn）提交，由依托单位审核后提交至自然科学基金委。自然科学基金委审核未通过者，将退回的电子版计划书修改后再行提交；审核通过者，打印纸质版计划书（一式两份，双面打印）并在项目负责人承诺栏签字，由依托单位科研、财务管理等部门审核、签章并在承诺栏加盖依托单位公章，且将申请书纸质签字盖章页订在其中一份计划书之后，一并报送至自然科学基金委项目材料接收工作组。纸质版计划书应当保证与审核通过的电子版计划书内容一致。**自然科学基金委将对申请书纸质签字盖章页进行审核，对存在问题的，允许依托单位进行一次修改或补齐。**

向自然科学基金委提交电子版计划书、报送纸质版计划书并补交申请书纸质签字盖章页截止时间节点如下：

1. **2023年9月7日16点：**提交电子版计划书的截止时间；
2. **2023年9月14日16点：**提交修改后电子版计划书的截止时间；
3. **2023年9月21日：**报送纸质版计划书（一式两份，其中一份包含申请书纸质签字盖章页）的截止时间。
4. **2023年10月7日：**报送修改后的申请书纸质签字盖章页的截止时间。

请按照以上规定及时提交电子版计划书，并报送纸质版计划书和申请书纸质签字盖章页，逾期不报计划书或申请书纸质签字盖章页且未说明理由的，视为自动放弃接受资助；未按要求修改或逾期提交申请书纸质签字盖章页者，将视情况给予暂缓拨付经费等处理。

附件：项目评审意见及修改意见表

国家自然科学基金委员会
2023年8月24日

21002905-1250

国家自然科学基金

资助项目准予结题通知

詹天明　同志：

您承担的国家自然科学基金项目：(面向土地资源审计的联合遥感图像融合与变化检测张量字典学习方法)，批准号：(61976117)按有关规定已审核完毕，准予结题。

与本项目资助有关的后续成果，请您继续及时报送。

祝您在研究工作中取得更好的成绩！

国家自然科学基金委员会

信息科学部

2024年3月26日

江苏省科技计划项目验收证书

苏科验字［2024］第 0361 号

计划类别：基础研究计划（自然科学基金）--面上项目

项目编号：BK20191409

项目名称：基于张量字典学习的联合遥感图像融合与变化检测方法

承担单位：南京审计大学

项目负责人：詹天明

发证日期：二〇二四年二月

扫码查验

江苏省科学技术厅
项目验收专用章

21201301-1014

国家自然科学基金

资助项目准予结题通知

詹天明　同志：

您承担的国家自然科学基金项目：(深度特征学习与空间特征联合约束的脑胶质瘤低秩分割方法)，批准号：(61502206)按有关规定已审核完毕，准予结题。

与本项目资助有关的后续成果，请您继续及时报送。

祝您在研究工作中取得更好的成绩！

国家自然科学基金委员会

信息科学部

信息科学部

2019年03月27日

项目编号：23KJA520009

江苏省高等学校 基础科学（自然科学）研究重大项目合同

（2023 年度）

项目名称	：	高标准农田审计中高光谱图像精细变化检测方法研究
项目负责人	：	詹天明
起止年限	：	2023 年 7 月～2026 年 7 月
所在学校	：	南京审计大学
填表日期	：	2023-09-11

江苏省教育厅

二〇二三年

江苏省科学技术厅文件

苏科区发〔2022〕291号

关于2022年第二批
江苏省产学研合作项目立项的通知

各设区市、县（市、区）科技局，各有关单位：

为深化产学研合作，鼓励全国高校院所与江苏企业联合开展科技研发，促进高校院所成果转化，推动江苏企业技术创新，根据《关于组织申报2022年江苏省科技副总项目的通知》（苏科区发〔2022〕58号）、《关于组织申报2022年第二批江苏省产学研合作项目的通知》（苏科区发〔2022〕189号）、《关于组织申报2022年江苏省产学研合作项目（揭榜挂帅）的通知》（苏科机发〔2022〕220号）精神，经申报推荐、资格审查、信用审查、网上公示等工作程序，省科技厅确定对《中高层大气探测激光雷达回波光谱采集软件开发》等889项“产学研合作项目”给予指导性计划立项。请各主管部门和承担单位加强项目的组织实施，保证项目按时完成。

2022 年第二批江苏省产学研合作项目立项表

项目编号	BY2022632	主管部门	南京市雨花台区科技局、南京市科技局	起止时间	2022-2023 年	项目负责人	蒋雪峰
项目名称	车载后勤保障设备用电机及其控制系统研发			项目类型	技术开发项目	已投入经费	30 万元
承担单位	南京理工大学			项目参加人员	周坤、孙武、王涛、王思远、魏之建		
合作单位	南京以禾电子科技有限公司						
项目内容和完成指标	本项目旨在研发一款新型电机及其控制系统，主要应用于车载后勤保障设备中，以提高保障设备的稳定性和可靠性。项目主要内容：（1）研究电机本体结构的设计方案。（2）研究电机控制系统的电路原理。（3）研究电机控制系统的功能模块，包括采样模块、控制模块和驱动模块等。（4）完成设备联调联试。主要完成指标：（1）研发出新型电机及其控制系统 1 套。（2）提供电机设计图纸、系统使用说明等全套技术资料。（3）申请专利 1-2 件。						
备注	蒋雪峰入选 2021 年科技副总项目。						

获奖证书

为表彰2021年江苏省高等学校科学技术研究成果奖获奖者，特颁发此证书，以资鼓励。

成果名称： 面向土地资源审计的高光谱图像分析方法

主要完成人： 詹天明　万鸣华　张道潘　孙周宝　宋博

主要完成单位： 南京审计大学

奖励等级： 三等奖

江苏省教育厅

二〇二一年十月

NO: J009061

河南省科学技术进步奖
证　　书

为表彰河南省科学技术进步奖获得者，特颁发此证书。

项目名称：融合多源遥感影像的国土空间智能监测与优化关键技术及应用

奖励等级：贰等奖

获 奖 者：詹天明

河南省人民政府

2024年12月8号

证书号：2024-J-135-R04/10