

附件 2:

2027 年推免资格申请表

姓名	赵宣昭	性别	男	出生年月日	2005.12.18	学号	2023013549											
民族	汉	籍贯	河南省（市、区）					濮阳县（市）										
身份证号	4	1	0	9	2	8	2	0	0	5	1	2	1	8	4	9	1	4
所在学院/专业学生人数				335/129				联系电话				18236036754						
何时、何地入党、入团				2024-07-05 年于西北农林科技大学信息工程学院入团														
何时、何地、因何原因 受过何种奖励				2024 年九月，在西北农林科技大学信息工程学院，因表现优异获得“优秀志愿者” 2024 年获得全国大学生数学建模竞赛省二等奖 2025 年四月十三日，在西北农林科技大学，因参与“杨凌马拉松”志愿服务工作表现优异获得“优秀志愿者” 2025 年五月，在西北农林科技大学，获得蓝桥杯全国软件和技术大赛省三等奖 2025 年十月，在西北农林科技大学信息工程学院，因表现优异获得“优秀负责人” 2025 年十月，在西北农林科技大学，获取全国大学生数字媒体科技作品及创意竞赛省二等奖 2026 年，获取美国大学生数学建模竞赛 H 奖 2026 年五月，在西北农林科技大学，获得中国大学生计算机设计大赛西北赛区一等奖 2026 年八月，获得中国大学生计算机设计大赛国家级三等奖														
所学外语语种		英语		通过最高级别		四级		成绩		485								
思想政治品德成绩		87.05		前三年学分成绩		79.01		前三年 学分成绩专业排名		56/129								
申请类型		学术特长生																
“本人保证提交的申请表和全部申请材料的真实性和准确性。如果提交的信息不真实或不准确，同意取消我的推荐免试资格。”																		
具有 2027 年招生资格的相关专业导师推荐意见： 签名：赵宣昭 2026 年 9 月 9 日																		
本科毕业学院党委对推免生思想政治考核意见： 签名：王美丽(代) 2026 年 9 月 9 日																		
本科毕业学院党委对推免生思想政治考核意见： 考察合格、同意推荐。 签字：谭东明 党委（盖章）																		



柴凤

2026年9月9日	
推荐单位对推免生的审核、评定意见： 同意推荐	签字：杨沛 单位名称（盖章） 2026年9月9日 信息工程学院
备注：	

注：1. 此表交本学院留存备查；
2. 若专项实施部门有专用的申请表，请用各专项实施部门的申请表；若专项实施部门没有申请表，申请专项推荐指标的学生须用此表，申请人应将审核盖章的表复印后，原件留存本学院，复印件交团委或党委学生工作部或教务处或“双一流”学科群。



姓名: 赵宣昭

性别: 男

学号: 2023013549

入学时间: 2023年09月01日

学院: 信息工程学院

专业: 软件工程

班级: 软件2304

学制: 四年



课程号		课程名	性质	学分	成绩	绩点	附注	课程号		课程名	性质	学分	成绩	绩点	附注
2023-2024学年 秋								2025-2026学年 秋							
1090000	新生研讨课		选修	1.0	94	--	补考	2095204	数据库综合实践	必修	2.0	91	4.0		
1091102	C语言程序设计		必修	3.5	68	2.0		ey058	创业法学	任选	1.0	98	--		
1092501	数字逻辑与数字系统		必修	3.0	71	2.3		ey092	中国现代文学名家名作	任选	1.0	98	--		
1095002	linux实践		必修	1.0	91	4.0		已获学分: 8.0 GPA: 3.9							
1151200	高等数学甲I (上)		必修	5.5	90	4.0		2025-2026学年 春							
1180012	思想道德与法治		必修	2.5	89	3.7		2092209	计算机网络	必修	3.0	69	2.0		
1191017	大学英语A1		必修	3.0	73	2.3		2094525	机器学习	选修	2.5	68	2.0		
1241001	体育I		必修	1.0	91	4.0		3093107	多媒体技术及应用	选修	2.5	91	4.0		
1301002	军事理论		必修	2.0	87	3.7		3093108	计算机图形学	选修	2.5	80	3.0		
1305103	军事技能训练		必修	2.0	99	4.0		3093115	数字图像处理	选修	2.5	78	3.0		
1306001	大学生心理健康与发展		必修	1.0	98	4.0	3093305	编译原理	必修	3.0	72	2.3			
2120138	生命与文学		任选	1.0	91	--	3093310	软件工程	选修	2.5	88	3.7			
ZH073	唐诗宋词人文解读		选修	1.0	75	--	3093501	软件体系结构	选修	2.5	83	3.3	补考		
已获学分: 27.5 GPA: 3.24								3095306	编译原理课程设计	必修	1.0	82	3.3		
2023-2024学年 春								3181007	毛泽东思想和中国特色社会主义理论体系概论	必修	2.5	69	2.0		
1085002	工程训练 (乙)		必修	2.0	88	3.7	已获学分: 24.5 GPA: 2.8								
1092104	面向对象程序设计		必修	3.0	73	2.3	2025-2026学年 春								
1151101	大学物理 (甲)		必修	5.0	69	2.0	3093109	计算机视觉	选修	2.5	75	2.7			
1151211	高等数学甲I (下)		必修	5.5	89	3.7	3093312	软件过程管理	必修	2.0	68	2.0			
1180008	改革开放史		任选	1.0	90	--	3093314	软件测试	必修	2.5	67	1.7			
1180013	焦点解决心理学与学生		任选	1.0	100	--	3094101	工程伦理	必修	1.0	89	3.7			
1181003	中国近现代史纲要		必修	2.5	83	3.3	3094520	深度学习	选修	2.0	75	2.7			
1191018	大学英语A2		必修	3.0	76	2.7	3095312	软件开发综合实践	必修	6.0	87	3.7			
1241002	体育II		必修	1.0	83	3.3	3181008	习近平新时代中国特色社会主义思想概论	必修	3.0	80	3.0			
1305202-1	劳动教育理论		任选	1.0	82	3.3	已获学分: 19.0 GPA: 2.91								
1306005	生涯规划与职业发展		必修	1.0	92	4.0	以下空白								
2092508	计算机组成原理		必修	3.0	77	2.7									
已获学分: 29.0 GPA: 2.95															
2023-2024学年 夏															
2095108	面向对象程序设计实践		必修	2.0	91	4.0									
ey136	人生风险与社会保障		任选	1.0	95	--									
已获学分: 3.0 GPA: 4.0															
2024-2025学年 秋															
1080113	农业智能装备与制造		任选	1.0	78	--									
1091201	数据库原理与应用		必修	3.0	79	3.0									
1300014	书法鉴赏		任选	1.0	84	--									
2091109	数据结构		必修	3.5	77	2.7									
2093305	Java语言程序设计		必修	3.0	99	4.0									
2151102	大学物理实验 (甲)		必修	1.5	84	3.3									
2151208	线性代数I		必修	2.5	81	3.0									
2151223	概率论与数理统计		必修	4.0	75	2.7									
2181003	马克思主义基本原理		必修	2.5	70	2.0									
2191028	考研英语		选修	1.5	80	3.0									
2241001	体育III		必修	1.0	89	3.7									
已获学分: 24.5 GPA: 2.97															
2024-2025学年 春															
1300009	音乐鉴赏		任选	1.0	86	--									
2092103	操作系统		必修	3.0	73	2.3									
2093202	Linux程序设计		必修	2.5	87	3.7									
2093308	面向对象系统分析与设计		选修	2.5	84	3.3									
2094401	Web技术及应用		选修	3.0	73	2.3									
2094513	嵌入式系统与应用		选修	2.5	66	1.7									
2095203	Linux程序设计综合实践		必修	1.0	83	3.3									
2191025	中国文化传播		选修	1.5	84	3.3									
2241002	体育IV		必修	1.0	92	4.0									
3092315	算法设计与分析		选修	2.5	78	3.0									
3095316	算法设计与分析综合实践		必修	1.0	88	3.7									
3153004	离散数学		选修	3.0	68	2.0									
ey201	人工智能		任选	1.0	99	--									
已获学分: 25.5 GPA: 2.77															
2024-2025学年 夏															
1185008	思想政治理论课实践		必修	2.0	86	3.7									
2095110	数据结构综合实践		必修	2.0	93	4.0									
已获总学分		161.0	校内修读学分					161.0	校外认定学分		0.0				
方案要求学分		171.0	GPA						3.0						
备注															

附件 8:

信息工程学院优秀应届本科毕业生 免试攻读研究生导师联名推荐信

尊敬的院推免生遴选工作小组:

赵宣昭同学为我院 2023 级软件工程专业本科生。现该同学准备攻读研究生，特予以推荐。

作为该同学《Java 程序设计》课程的教师，在授课过程中，我发现该生学习态度端正，课堂认真听讲。在实验课中，可以灵活应用所学知识，表现出较强的动手能力。

该生积极参加各类学科竞赛，曾获得第 16 届蓝桥杯程序设计大赛陕西赛区三等奖、2024 年全国大学生数学建模竞赛陕西赛区二等奖、2026 年美国大学生数学建模竞赛 H 奖、2026 年第六届全国计算机设计大赛国家级三等奖等诸多奖项。

该生科研兴趣浓厚，参与 2024 年国家级科创项目"基于耕地遥感图像变化检测"项目，在此期间获批软著一项，并在本科阶段作为第三作者发表了 CCF C 论文一篇。

鉴于赵宣昭同学在本科阶段的出色表现，以及该生在科研领域具有的较大发展潜力和培养前途，我推荐该生参加本次信息工程学院 2027 年推荐优秀应届本科毕业生免试攻读硕士学位研究生。

推荐人：

毛锐 杨丽丽
王美丽

日期：2026.9.9.

论文录用证明

尊敬的老师您好:

我们的论文《TeLE-Net: A Texture-Enhanced Line Extraction Network》已经被 CASAXR 2026 (原 CASA, CCF C 类论文) 收录进 CASAXR 会议论文集, 但由于出版社问题还未能检索, 现附上材料若干, 请您审阅。

第一作者: 鲁方博

第二作者: 罗万阔

第三作者: 赵宣昭

指导老师签字: 王美丽

日期: 2026.9.9

论文录用邮件通知:

CASAXR 26 notification for paper 22

CASAXR 26

Dear Fangbo Lu,

Thank you for submitting your paper to CASAXR 26.

Due to the large number of high-quality submissions, we are pleased to inform you that your paper 22: "TeLE-Net: A Texture-Enhanced Edge Extraction Network," has been selected for full presentation at the CASAXR 26 conference.

However, please note that your paper will not be published in the journal CAWV. Instead, it has been recommended for publication in the CASAXR 2026 Proceedings, in the Lecture Notes in Computer Science (LNCS) series, published by Springer (EI-indexed).

We sincerely acknowledge the significant effort and dedication you have invested in your research and greatly appreciate your contribution to CASAXR 26.

To proceed with the publication process, we kindly invite you to revise your paper in accordance with the reviewers' comments provided in the CASAXR 26 review reports as below. The revised version should be submitted by May 5, 2026.

Please confirm by email to casaxr26@miralab.ch whether you agree to revise your paper for publication in the CASAXR 2026 LNCS proceedings.

Please note that without your confirmation, your paper cannot be included in the conference program and will be withdrawn from consideration.

Thank you very much for your contribution. We look forward to your response.

Kind regards,

CASAXR 26 Program Chairs

SUBMISSION: 22

TITLE: TeLE-Net: A Texture-Enhanced Edge Extraction Network

----- REVIEW 1 -----

SUBMISSION: 22

TITLE: TeLE-Net: A Texture-Enhanced Edge Extraction Network

----- Overall evaluation -----

SCORE: 1 (weak accept)

----- TEXT:

Strengths:

1. Reasonable architectural design.

'Texture Self-Enhancement Module (TSEM)' is designed as the integration of gradient features and the attention mechanism, which is reasonable.

'Coord-Attention' is incorporated for effectively identifying and eliminating continuous noise.

2. Experimental results are good.

The results are excellent, and the experiments are well conducted.

Weaknesses:

The introduction is not very clear. First, the introduction claims that existing approaches suffer from "structural artifacts, edge discontinuities, and heavy reliance on post-processing", but does not analyze why these problems occur.

Weaknesses:

The introduction is not very clear. First, the introduction claims that existing approaches suffer from "structural artifacts, edge discontinuities, and heavy reliance on post-processing", but does not analyze why these problems occur.

Second, the authors raise the issue in the field: "extracting structurally complete and semantically consistent edge representations within complex noisy environments", but do not specify to what extent this issue has been addressed in this article.

----- Originality -----

Sounds ok.

----- State-of-the-Art -----

Fair.

----- Quality of the text -----

SCORE: 4 (good)

----- TEXT:

The text reads well.

----- Results -----

SCORE: 4 (good)

----- TEXT:

No video.

----- REVIEW 2 -----

SUBMISSION: 22

TITLE: TeLE-Net: A Texture-Enhanced Edge Extraction Network

----- Overall evaluation -----

SCORE: -2 (reject)

----- TEXT:

The paper discusses edge detection, using a novel U-net architecture with attention in its bottleneck. As specified below, motivation for the problem is unclear, the writing lacks in several ways, there is little to no contribution, the positioning with the state-of-the-art is partial at best, and results are underwhelming. Hence there is not much reason to support publication unfortunately.

----- Originality -----

The paper presents an elaborate architecture with several components. Some of these components are uncommon, and hence may suggest originality, however since their motivation and justification is unclear, it is hard to assess the contribution of the paper.

----- State-of-the-Art -----

The paper compares to a small set of papers, with only one from 2025. To me, the most obvious baseline would be a LoRA trained over an image generator like QWEN and/or Flux2. Without such baselines, or motivation of why this baseline is irrelevant, there is no place for publication.

For feature extraction, it is unclear why DiNo (Learning Robust Visual Features without Supervision) isn't employed, and not even mentioned, let alone its vast related literature on feature enhancement (e.g., LoftUp, anyUp, FAR, etc).

图书馆检索:

集成检索

操作提示

标题检索支持Web Of Science, EI, CSD, CNKI, 万方, 维普数据库的在线检索, 检索时支持模糊检索, 最多返回网站检索结果的前50条。

标题

TeLE-Net: A Texture-Enhanced Line Extraction Network

清除

检索

数据库:

☐ Web of Science

☒ EI

☐ Scopus

☐ PubMed

☐ CSD

☐ CSSCI

☐ CNKI

☐ 万方

年度范围:

1990

2028

若检索结果为灰色(不可选), 代表该标题未被所选数据库收录, 请先访问所选数据库主页, 确认文章已被收录后再提交检索。

若检索结果为黄色(未默认勾选), 代表该标题在该数据库检索到多条文献, 请点开标题前面的加号, 勾选需要的文献。

若检索结果为绿色(默认勾选), 代表该标题在该数据库检索1条文献, 可点开标题前面的加号, 确认检索结果。

共返回 1 组

文献详情

TeLE-Net: A Texture-Enhanced Line Extraction Network

总数: 1 组

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1

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10 条/页

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导入

TeLE-Net: A Texture-Enhanced Line Extraction Network

Fangbo Lu, Wanchuang Luo, Xuanzhao Zhao, Yulin Feng, Ding Liang,
Xiaokun Sun, and Meili Wang

Northwest A&F University, China
wml@nwsuaf.edu.cn

Abstract. Edge detection, as a fundamental low-level vision task and the core preprocessing step for XR/AR virtual-real registration, non-photorealistic rendering, cartoon animation contour extraction and other related topics, aims to extract object boundaries with rich structural and semantic information from images. To alleviate its performance degradation in complex noisy scenes, we propose the Texture-enhanced Line Extraction Network (TeLE-Net), an encoder-decoder architecture built with the Spatial Residual U-block (SRSU) as its core module, together with a designed Texture Self-Enhancement Module (TSEM). Extensive experimental results demonstrate that TeLE-Net generates edge maps with high signal-to-noise ratio and complete structural integrity on the mainstream BIPED and BSDS500 datasets, without any post-processing operations. It achieves OIS scores of 0.930 and 0.862 on the two datasets respectively, comprehensively outperforming existing state-of-the-art (SOTA) methods. With only 21.6M parameters, our method can be directly deployed in real-time XR and graphics rendering pipelines.

Keywords: Edge Detection, Texture Enhancement, Multi-scale Feature Fusion, Attention Mechanism

1 Introduction

Edge detection is a fundamental task in computer vision that aims to extract object boundaries with abundant structural and semantic information[1]. As an essential low-level vision operation, it also acts as a critical preprocessing step for XR/AR virtual-real registration, non-photorealistic rendering (NPR), and contour extraction of cartoon animation. With the advancement of deep learning, research focus in this field has shifted from early handcrafted operator-based local gradient analysis to deep neural network-driven multi-scale feature fusion and representation learning [2, 3].

However, under complex noise and texture interference, existing methods suffer from three core limitations: First, structural artifacts and edge discontinuities result from direct shallow-stage raw image feature extraction (lacking explicit high-frequency noise-structural texture decoupling), leading to layer-wise noise

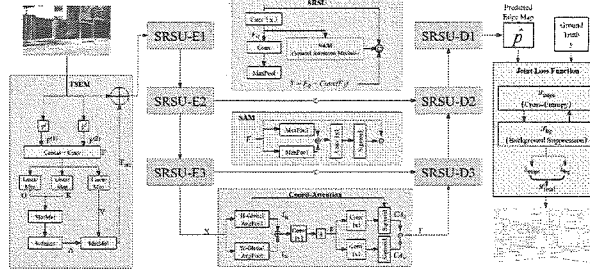


Fig. 1. The overall architecture of the proposed TeLE-Net.

accumulation, distorted edge features, and disrupted global structural consistency due to discarded spatial coordinate information in global average pooling. Second, heavy reliance on post-processing is required, as raw edge probability maps have low SNR and background pseudo-responses (inadequate end-to-end noise suppression), necessitating additional steps (non-maximum suppression, edge linking, morphological operations) that increase pipeline complexity and hinder real-time XR/graphics deployment. Thus, extracting structurally complete and semantically consistent edges in complex noisy environments is an urgent critical issue in current edge detection research.

2 Related Work

2.1 Traditional Edge Detection Methods

Early edge detection methods primarily relied on the response of local differential operators to variations in grayscale or brightness[4]. The Canny operator established a classic and theoretically grounded edge detection pipeline through steps including Gaussian smoothing, gradient calculation, non-maximum suppression, and double-threshold hysteresis [5].

To incorporate richer local contextual information, Structured Forests utilize a random decision forest framework to perform structured learning on local image patches, directly predicting local edge masks. This approach enhances the modeling of local structural patterns to a certain degree [6]. Nevertheless, both operator-based methods relying on gradient responses and structured models based on shallow learning primarily depend on color or brightness variations for feature discrimination, resulting in a lack of high-level semantic understanding of the image content. In natural scenes characterized by complex textures or significant noise, these methods are prone to misclassifying background textures as genuine boundaries. Furthermore, they often necessitate additional post-processing steps—such as smoothing, edge linking, or morphological operations—making it difficult for them to serve as stable structural priors.

2.2 Deep Learning-based Edge Detection

With the advancement of deep learning, edge detection has evolved from local responses based on hand-crafted features toward end-to-end feature learning. Early deep architectures, such as DeepEdge [7] began leveraging multi-scale convolutional features and high-level semantic information for contour prediction, demonstrating the critical role of deep features in edge discrimination. HED established a fundamental paradigm by proposing an end-to-end holistically-nested framework, which effectively addresses edge scale diversity through side-output layers and deeply supervised learning.

Under this paradigm, researchers have continuously explored more sophisticated hierarchical feature fusion strategies. BDCN introduces scale-specific supervision and scale enhancement modules, allowing features at different levels to maintain distinct roles during training [8]. while DexiNed focuses on generating crisper, more continuous boundaries through a lean network structure with robust generalization capabilities [9]. To mitigate edge blurring and localization bias, Deep Crisp Boundaries employs a top-down hierarchical refinement pathway to enhance precision and clarity [10]. As model complexity grows, efficiency and deployment costs have become pivotal; consequently, lightweight designs like PiDiNet, LDC, and TEED achieve high-performance edge detection with minimal parametric and computational overhead [11–14].

Regarding advanced architectures, EDTER incorporates the global attention mechanism of Transformers [15] to model long-range dependencies, balancing global semantic consistency with local detail [16]. More recently, DiffusionEdge reformulates edge detection as a progressive generative process, utilizing the denoising mechanism of diffusion models to produce superior edge representations [17]. Despite these performance gains on benchmarks, existing methods still struggle in complex environments, where results may suffer from structural fragmentation or artifacts due to noise interference and local instabilities.

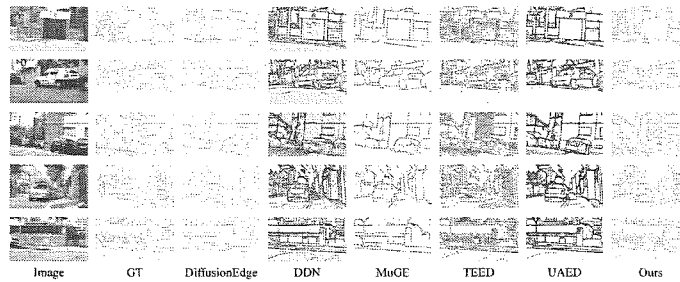


Fig. 2. Comparisons on the BIPED Dataset

2.3 Feature Enhancement and Attention Mechanisms

To further enhance the robustness and controllability of edge representation, research attention has shifted toward feature enhancement, attention mechanisms, and uncertainty modeling.

UAED explicitly models the subjectivity and ambiguity inherent in edge annotation as probability distributions, characterizing uncertainty regions via variance and applying adaptive weighting during training to bolster robustness in complex scenes [18]. Addressing the subjectivity in edge granularity, MuGE proposes a multi-granularity edge generation framework, enabling the model to output results at varying levels of detail [19]. Furthermore, DDN performs disentanglement modeling at both data and feature levels; by separating learnable distributions from spatial/semantic features, it mitigates redundant interference and enhances generalization capabilities [20].

At the semantic level, CaseNet extends edge detection to a multi-label semantic edge problem, allowing a single boundary to be associated with multiple semantic categories [21]. These approaches demonstrate that fine-grained control over feature representation contributes significantly to the stability and semantic consistency of edge results. Despite the progress achieved by existing methods in feature fusion, two prevalent limitations remain when addressing complex scenarios:

Current Limitations of Existing Methods: Existing networks typically perform feature extraction directly on raw images without explicitly disentangling high-frequency noise from structural textures in the shallow stages, which leads to progressive accumulation of noise interference across layers. In addition, in deep networks, simple global average pooling tends to discard spatial coordinate information and lacks effective noise gating mechanisms, making it difficult for the decoder to simultaneously suppress background noise and accurately recover globally consistent structural boundaries.

To address the above limitations, this paper proposes TeLE-Net, an end-to-end edge detection network tailored for complex noisy environments and real-time graphics/XR scenarios. The core contributions include: designing the TSEM for shallow feature stage, which integrates multi-order gradient priors and structure-aware self-attention to realize explicit noise-texture disentanglement and provide robust geometric priors; adopting SRSU as the core feature extraction unit, which combines nested U-structure and lightweight spatial attention to balance receptive field expansion and pixel-level edge localization accuracy, improving edge fine-grained feature representation; introducing Coordinate Attention (CA) in the semantic exchange stage to encode spatial positional information into channel-wise relationships, strengthening global structural consistency and removing continuous noise streaks; proposing a joint loss function with pseudo-response suppression (PRS) loss to suppress background noise in training, enabling the model to generate high-SNR edge maps without post-processing.

3 Proposed Method

3.1 Overall Architecture

As illustrated in Figure 1, TeLE-Net adopts an end-to-end encoder-decoder architecture. Unlike conventional methods that rely heavily on post-processing, it uses SRSU as the core feature extractor and improves representation through multi-scale feature enhancement. Given an input image $\mathbf{I} \in \mathbb{R}^{H \times W \times 3}$, the network generates a high-SNR edge probability map. It integrates TSEM to suppress noise via gradient-aware structural perception, SRSU blocks with pixel-wise attention for multi-scale feature encoding, and CA to strengthen global structural consistency. In the decoding stage, multi-scale feature fusion and a noise suppression loss are used to produce the final edge maps.

3.2 Texture Self-Enhancement Module

To address the sensitivity of convolutional networks to noise in shallow layers and the ambiguity of structural information in deep layers, we design the TSEM. Unlike existing edge detection methods that lack explicit texture enhancement and noise-texture disentanglement in the shallow network stage (leading to the accumulation of noise interference in deep layers) and only use single gradient operators or attention mechanisms alone, TSEM combines the explicit geometric prior of multi-order gradient features with the long-range dependency modeling capability of self-attention. This enables it to achieve adaptive enhancement of texture features while eliminating high-frequency noise.

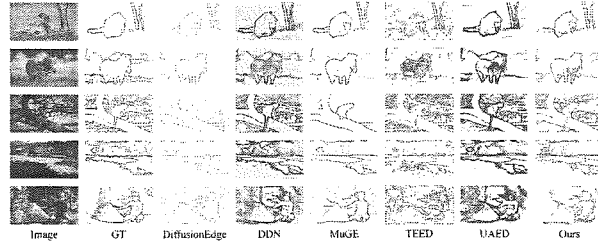


Fig. 3. Comparisons on the BSDS Dataset

Gradient-Induced Feature Embedding First, TSEM extracts multi-order gradient information within the input feature space using gradient operators. Specifically, we apply the Sobel operator $\mathcal{K}_{sobel}$ and the Laplacian operator $\mathcal{K}_{lap}$ to the input features to extract first-order edge gradients $\mathbf{G}_1$ and second-order texture details $\mathbf{G}_2$, respectively:

$$\mathbf{G}_1 = \mathcal{K}_{sobel}(\mathbf{X}_{gray}), \mathbf{G}_2 = \mathcal{K}_{lap}(\mathbf{X}_{gray}). \quad (1)$$

To incorporate these structural priors into the feature space, we concatenate the original features with the gradient maps and map them through a fusion layer $\mathcal{F}_{fuse}$ to yield the feature map $\mathbf{F}$, which is enriched with structural information:

$$\mathbf{F} = \text{ReLU}(\text{BN}(\mathcal{F}_{fuse}([\mathbf{X}_{gray}, \mathbf{G}_1, \mathbf{G}_2]))), \quad (2)$$

Structure-Aware Self-Attention Mechanism Since the preceding process remains insufficient to distinguish high-frequency noise, TSEM subsequently introduces a convolutional self-attention mechanism to eliminate such noise by leveraging long-range dependencies. Specifically, the feature map $\mathbf{F}$ is projected into Query, Key, and Value matrices—denoted as $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$ —via three 1×1 convolutions:

$$\mathbf{Q} = W_\theta(\mathbf{F}), \quad \mathbf{K} = W_\phi(\mathbf{F}), \quad \mathbf{V} = W_g(\mathbf{F}). \quad (3)$$

We compute the similarity between $\mathbf{Q}$ and $\mathbf{K}$ to generate the structural attention map $\mathbf{A}$, which is subsequently applied to $\mathbf{V}$ to aggregate global contextual information:

$$\mathbf{A}_{i,j} = \frac{\exp(\mathbf{Q}_i \cdot \mathbf{K}_j^T)}{\sum_j \exp(\mathbf{Q}_i \cdot \mathbf{K}_j^T)}, \quad \mathbf{Y} = \mathbf{A} \cdot \mathbf{V}. \quad (4)$$

Finally, the enhanced texture features $\mathbf{Y}$ (projected by the linear transformation W_{out}) are added back to the original input $\mathbf{X}$ via a residual connection, yielding the final output.

3.3 Spatial Residual U-block

The fundamental building block of TeLE-Net is the SRSU. Designed as a modified Residual U-block[22], the SRSU adopts a nested sub-encoder-decoder architecture. This design aims to address the limited receptive field of single convolutional layers while ensuring the extraction of line features with pixel-level precision. To achieve a high Signal-to-Noise Ratio in the output and mitigate the reliance on post-processing, the SRSU incorporates a lightweight SA mechanism at its highest-resolution feature aggregation layer[23]. The primary objective of SA is to enhance local feature saliency by modeling inter-pixel spatial correlations. Specifically, given the input feature map $\mathbf{x}$ at this level, we first conduct Average Pooling and Max Pooling operations along the channel axis to aggregate spatial context descriptors from different dimensions:

$$\mathbf{x}_{avg} = \text{mean}(\mathbf{x}, \text{dim} = 1), \quad \mathbf{x}_{max} = \text{max}(\mathbf{x}, \text{dim} = 1). \quad (5)$$

Subsequently, the two resulting single-channel feature maps are concatenated and processed by a 1×1 convolutional layer to learn the spatial weight distribution. This yields the pixel-wise attention map S , which is finally applied to the original feature map to assign dynamic weights:

$$S = \sigma(\mathcal{F}_{1 \times 1}([\mathbf{x}_{avg}, \mathbf{x}_{max}])), \quad \mathbf{x}_{out} = \mathbf{x} \otimes S. \quad (6)$$

Table 1. QUANTITATIVE COMPARISONS ON THE BIPED DATASET.

Methods	Single-scale		AC $\uparrow$	PE $\uparrow$	Params (M) $\downarrow$
	ODS $\uparrow$	OIS $\uparrow$			
RCF [24]	0.843	0.859	—	—	14.8
EDTER [16]	0.893	0.898	—	—	468.8
TEED [13]	0.867	0.871	0.334	0.185	0.1
UAED [18]	0.819	0.839	0.261	0.207	72.5
MuGE [19]	0.707	0.730	0.302	0.259	278.4
DiffusionEdge [17]	0.899	0.901	0.442	0.413	225.0
DDN [20]	0.915	0.922	0.286	0.101	41.2
TeLE-Net (ours)	0.925	0.930	0.346	0.334	21.6

3.4 Coord-Attention

Traditional channel attention mechanisms focus on modeling inter-channel dependencies but ignore spatial positional information, making it difficult to distinguish between real edges and structured noise streaks—especially in complex imaging environments where noise rarely exists as isolated pixels but often manifests as continuous "noise streaks." Unlike Rotary Position Embedding (RoPE), which is designed for 1D sequence modeling in Transformers, CA can directly encode the 2D spatial coordinate information of convolutional feature maps into channel-wise relationships; thus, TeLE-Net incorporates an improved CA module to enable the network to achieve high-dimensional semantic discrimination of texture features while enhancing global structural consistency, effectively identifying and eliminating continuous noise.

Specifically, CA decomposes the traditional global pooling operation into two parallel 1D feature encoding processes. For a given input feature map $\mathbf{x} \in \mathbb{R}^{C \times H \times W}$, we aggregate features along the horizontal and vertical coordinate directions using pooling kernels of size $(H, 1)$ and $(1, W)$, respectively. The output of the c -th channel at height h and width w can be formulated as:

$$f_c^h(h) = \frac{1}{W} \sum_{0 \leq i < W} x_c(h, i), f_c^w(w) = \frac{1}{H} \sum_{0 \leq j < H} x_c(j, w). \quad (7)$$

To effectively fuse multi-directional positional information, we concatenate the vertical feature map with the transposed horizontal feature map and employ a shared point-wise convolution to generate the intermediate latent representation $\mathbf{y} \in \mathbb{R}^{\hat{C} \times (H+W) \times 1}$:

$$\mathbf{y} = \sigma_{relu} (\mathcal{F}_1 ([\mathbf{f}^h, \text{permute}(\mathbf{f}^w)])) \quad (8)$$

Here, $[\cdot, \cdot]$ denotes the concatenation operation along the spatial dimension (specifically, the height dimension). $\hat{C} = \max(8, C/r)$ represents the reduced channel dimension. In this work, we set the reduction ratio to $r = 32$ to strike a balance between computational efficiency and representational power.

Subsequently, the intermediate feature map $\mathbf{y}$ is split along the spatial dimension into two separate tensors: $\mathbf{y}^h \in \mathbb{R}^{\hat{C} \times H \times 1}$ and $\mathbf{y}^w \in \mathbb{R}^{\hat{C} \times 1 \times W}$. These tensors are then mapped back to the original channel dimension C via two independent 1×1 convolutions, denoted as $\mathcal{F}_h$ and $\mathcal{F}_w$, respectively. Finally, the Sigmoid activation function σ is applied to generate the direction-aware attention weights $\mathbf{g}^h$ and $\mathbf{g}^w$.

Embedded within the deep semantic exchange stage, the CA module functionally serves as a “semantic gate,” filtering high-level semantic noise by modeling global consistency. Ultimately, the generated direction-aware weights are applied to the input feature map:

$$out_c(i, j) = x_c(i, j) \times g_c^h(i) \times g_c^w(j) + x_c(i, j) \quad (9)$$

3.5 Joint Loss Function

TeLE-Net is trained in an end-to-end manner employing a joint supervision strategy. The training objective integrates a multi-scale cross-entropy loss with a pseudo-response suppression loss, which is specifically designed to further suppress residual noise within background regions. The overall loss function is formulated as follows:

$$\mathcal{L}_{total} = \sum_{k=0}^K w_k \cdot \ell_{bce}(\sigma(d_k), \mathbf{G}_{gt}) + \lambda \cdot \mathcal{L}_{prs}, \quad (10)$$

Here, d_k denotes the side output prediction at the k -th scale, $\mathbf{G}_{gt}$ represents the ground truth edge map, $\sigma(\cdot)$ is the Sigmoid activation function, and w_k serves as the balancing weight for each scale.

We utilize the ground truth $\mathbf{G}_{gt}$ to construct a background mask. Specifically, this mask is generated by thresholding the labels to exclusively retain non-edge regions, based on which we define the Pseudo-Response Suppression (PRS) loss $\mathcal{L}_{prs}$ as follows:

$$\mathbf{M}_{bg} = \mathbb{I}(\mathbf{G}_{gt} < \tau), \mathcal{L}_{prs} = \ell_{bce}(\sigma(d_0) \odot \mathbf{M}_{bg}, \mathbf{0}). \quad (11)$$

Here, $\mathbb{I}(\cdot)$ denotes the indicator function, $\odot$ represents the element-wise multiplication (Hadamard product), and d_0 corresponds to the final high-resolution prediction output.

4 Experiments and Analysis

4.1 Datasets and Implementation Details

General Edge Detection Datasets: First, the BSDS500 dataset is widely employed as a standard benchmark for edge detection evaluation. It comprises 200 training images, 100 validation images, and 200 test images. Additionally, to assess model performance in high-resolution scenarios, we utilize the BIPED

Table 2. QUANTITATIVE COMPARISONS ON THE BSDS500 DATASET.

Methods	Single-scale		AC $\uparrow$	PE $\uparrow$	Params (M) $\downarrow$
	ODS $\uparrow$	OIS $\uparrow$			
RCF [24]	0.798	0.815	–	–	14.8
EDTER [16]	0.824	0.841	–	–	468.8
TEED [13]	0.664	0.680	0.290	0.175	0.1
UAED [18]	0.829	0.847	0.246	0.162	72.5
MuGE [19]	0.831	0.847	0.301	0.252	278.4
DiffusionEdge [17]	0.834	0.848	0.428	0.379	225.0
DDN [20]	0.842	0.858	0.302	0.099	41.2
TeLE-Net (Ours)	0.840	0.862	0.324	0.301	21.6

dataset, which consists of 250 high-resolution images meticulously annotated by experts (split into 200 for training and 50 for testing). For both datasets, we adopt the data augmentation strategy described in DDN [20].

Implementation Details: The model is implemented using the PyTorch framework and optimized via the Adam optimizer. The initial learning rate is set to 1×10^{-3} , with a batch size of 5. The model is trained for a total of 100 epochs. In the loss function calculation, the weight λ for $\mathcal{L}_{prs}$ is set to 0.1.

Evaluation Metrics To comprehensively evaluate model performance, we adopt the F-measure at both the Optimal Dataset Scale (ODS) and Optimal Image Scale (OIS) as the primary evaluation metrics. Furthermore, given that the F-measure primarily focuses on pixel-level classification accuracy following binarization, it may fail to fully capture the purity and energy distribution of the raw probability maps. Consequently, we introduce Average Clarity (AC) and Prediction Efficiency (PE) to assess the signal-to-noise ratio and confidence of the model outputs. AC is defined as the ratio of the sum of pixel intensities after Non-Maximum Suppression (NMS) to the total energy of the raw probability map P_{raw} (i.e., $AC = \sum NMS(P_{raw} / \sum P_{raw})$), serving as a metric for the sharpness of the edge response. PE quantifies the energy contribution of valid edges, defined as the ratio of the sum of raw prediction intensities at the positions of the binary skeletons extracted under ODS to the total energy of the probability map:

$$PE = \frac{\sum_{i=1}^H \sum_{j=1}^W P_{raw}(i, j) \cdot S_{ods}(i, j)}{\sum_{i=1}^H \sum_{j=1}^W P_{raw}(i, j)}, \quad (12)$$

Here, H and W denote the height and width of the image, respectively; $P_{raw}(i, j) \in [0, 1]$ represents the raw probability value output by the model; and $S_{ods}(i, j) \in \{0, 1\}$ signifies the refined skeleton mask generated at the ODS threshold. Higher values of AC and PE indicate that the model effectively suppresses background noise and yields highly focused edge responses, thereby reflecting the high confidence of the generated results and a reduced dependency on complex post-processing procedures.

4.2 Comparative Experiments on Edge Detection

Results Analysis on the BIPED and BSDS500 Datasets: In the quantitative evaluation on the high-resolution BIPED dataset (see Table 1), TeLE-Net achieves superior overall performance and reaches SOTA level. Under the Single-Scale (SS) setting, it attains **0.925** ODS and **0.930** OIS, outperforming methods such as DDN (0.915 ODS) and DiffusionEdge (0.899 ODS). These results validate the effectiveness of the pixel-wise spatial attention in the SRSU module. Although DiffusionEdge performs well in edge sharpness (AC/PE), its ODS is still 2.6% lower than TeLE-Net, indicating weaker localization accuracy. DDN also shows competitive ODS but has a much lower PE (0.101 vs. 0.334), indicating misalignment in edge localization. Overall, TeLE-Net achieves higher ODS/OIS with only 21.6M parameters, which is 4.6% of EDTER’s and 9.6% of DiffusionEdge’s, demonstrating a better balance of performance, precision, and lightweight design. As shown in Table 2, TeLE-Net also achieves state-of-the-art performance on BSDS500, obtaining an ODS of **0.840** and an OIS of **0.862** under SS evaluation, with OIS ranking first among all methods. This indicates that TeLE-Net effectively bridges the gap between quantitative metrics and visual quality. Although DDN has comparable ODS, its low PE (0.099) suggests overly coarse edges. In contrast, DiffusionEdge achieves higher AC (0.428) but underperforms in ODS/OIS. By leveraging the TSEM module to disentangle structure and texture features, TeLE-Net improves edge purity (PE = 0.301) and suppresses texture noise while maintaining strong localization accuracy. This balance between sharpness and accuracy shows that TeLE-Net remains competitive even against the heavyweight EDTER (468.8M parameters) under a lightweight setting.

Qualitative Analysis As illustrated in Fig. 2 and Fig. 3, TeLE-Net generates edge maps with exceptionally clean backgrounds, even in complex scenarios. This validates the significant efficacy of **Coord-Attention** and the **PRS loss function** in suppressing continuous noise streaks.

Table 3. Component Ablation Studies on the BIPED Dataset.

Index	1	2	3	4	5	6	7	8
TSEM		✓			✓	✓		✓
SRSU			✓		✓		✓	✓
CA				✓		✓	✓	✓
ODS(SS)	0.870	0.887	0.892	0.906	0.898	0.918	0.921	0.925

Ablation Analysis: As shown in Table 3, each core module contributes positively to the model performance, with significant synergistic effects among them. Specifically, incorporating the TSEM, SRSU, or CA modules independently boosts the ODS to 0.887, 0.892, and 0.906, respectively, validating the effectiveness of shallow geometric priors, multi-scale residual modeling, and global dependency capturing in edge detection. TSEM provides a noise-suppressed,

texture-enhanced (more salient) feature space for the subsequent CA module to improve global structural modeling efficiency, while the combination of SRSU and CA balances local edge detail preservation and global structural consistency. Ultimately, the full model integrating all three modules (index 8) achieves the highest ODS score of 0.925, verifying that our progressive structural modeling mechanism at different network levels can effectively generate structurally continuous, semantically consistent high-quality edges while suppressing noise.

5 Conclusion

In this paper, we propose TeLE-Net for edge detection in complex noisy scenarios. By disentangling noise and edges through TSEM, capturing fine-grained details with SRSU, and enhancing structural consistency via CA, TeLE-Net achieves SOTA performance on the BSDS500 and BIPED datasets.

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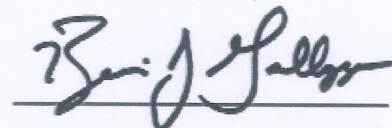
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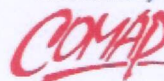
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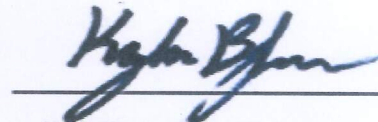
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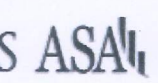
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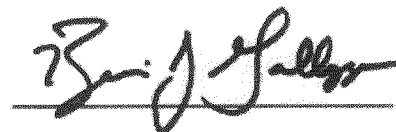
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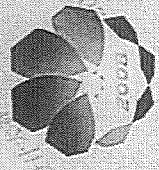
王美丽



2025年5月26日

王美丽
2026.9.7

获奖证书



西北农林科技大学作品《ImageForge——多模型协作的数字艺术创作系统》在
2026年（第19届）中国大学生计算机设计大赛中荣获

三等奖

参赛学生：乔永源、赵宣昭、王景涵
指导教师：王美丽
证书编号：2026091325



荣誉证书

王美丽
2026.9.7

HONORARY CERTIFICATE

西北农林科技大学 作品《ImageForge - 多模型协作的数字艺术创作系统》在 2026 年中国大学生计算机设计大赛西北地区赛中荣获

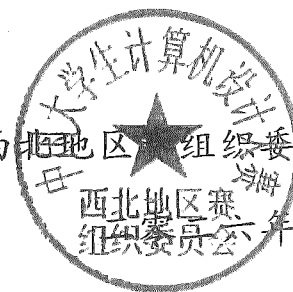
壹等奖

参赛学生：乔永源 赵宣昭 王景涵

指导教师：王美丽

证书编号：XBS-26-4529

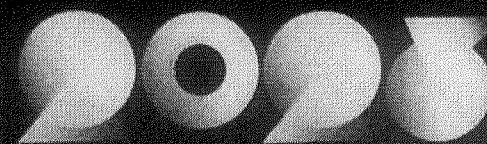
中国大学生计算机设计大赛西北地区组织委员会



西北赛区组织委员会
2026年五月

2025 (第十三届)

China College Student Digital Media Technology
Works and Creativity Competition



王美丽
2026.9.7

陕西赛区:

二等奖

参赛学校: 西北农林科技大学

参赛作品: 《创新之光·中国故事》

作品分类: 科技+创意, 讲好中国故事

指导老师: 王美丽

团队成员: 寇意、张帅、田俊果、王瑞衡、赵宣昭

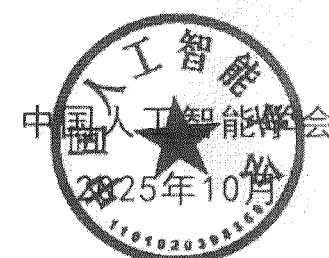
作品赛道: 本科及以上学历



证书编号
20252025405



关注微信公众号





2024

全国大学生数学建模竞赛

获奖证书

西北农林科技大学

学 生：韩锦炆，赵宣昭，李柳燕

指导教师：张倩倩

荣获

本科组陕西赛区二等奖

张倩倩

中国工业与应用数学学会
全国大学生数学建模竞赛陕西赛区组织委员会

2024年12月委员会

全国大学英语四级考试 成绩报告单



河南洛阳2823 060301150157

姓名: 赵宣昭
学校: 西北农林科技大学
院系: 信息工程学院
身份证号: 410928200512184914

笔 试

准考证号: 610061241108109

考试时间: 2024年6月

总分	听力 (35%)	阅读 (35%)	写作和翻译 (30%)
485	137	180	168

口 试

准考证号: --

考试时间: --

成绩	--
----	----

成绩报告单编号: 241161006005642



校验码: RP8T EPW7 ESCO ZGH5

说 明

- 全国大学英语四、六级考试(CET)是由教育部主办的全国统一考试,考试对象为在校大学生。考试内容包括听、说、读、写、译等语言技能。
- CET笔试考试时间为每年6月和12月;CET口试考试时间为每年5月和11月。
- 考生可登录中国教育考试网(www.neea.edu.cn)查询、下载电子成绩报告单或自行办理纸质成绩证明。电子成绩报告单和纸质成绩证明与纸质成绩报告单具有同等效力。

大学英语四级口语考试能力描述

优秀	能用英语就熟悉的话题进行有效的交流;能清晰地叙述或描述一般性事件和现象。语言表达清楚连贯。
良好	能用英语就熟悉的话题进行交流;能叙述或描述一般性事件和现象。语言表达基本准确。
合格	能用英语就熟悉的话题进行简单交流;能简单叙述或描述一般性事件和现象。

唐涛

中华人民共和国国家版权局 计算机软件著作权登记证书

证书号： 软著登字第17301648号

软件名称： 基于CNN transformer联合网络的耕地图像变化检测结果可视化分析软件
V1.0

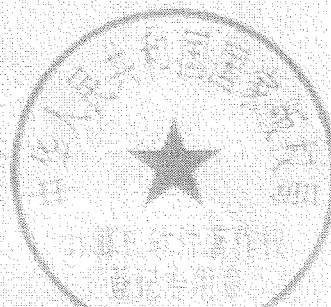
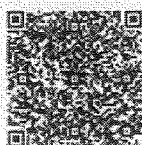
著作权人： 西北农林科技大学

权利取得方式： 原始取得

权利范围： 全部权利

登记号： 2026SR0087367

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2026年01月14日

计算机软件著作权申报证明

基于 CNN transformer 联合网络的耕地图像变化检测结果可视化分析软件 1.0，登记号为：2026SR0087367 的计算机软件著作权已于 2026 年 1 月 14 日登记下证

其开发技术人员排序为：赵宣昭、郭美旺

特此证明！

指导老师：廖清

大学生竞赛贡献证明

乔永源同学主持，赵宣昭、王景涵同学参与的国家级竞赛，竞赛名称为“中国大学生计算机设计大赛”，获奖等级为国家级三等奖，指导教师为王美丽，竞赛贡献排序如下：

竞赛主要贡献者：

计算机科学与技术硕士2601班

乔永源同学

学号：2026051089

竞赛其他贡献者：

软工2304班

赵宣昭同学 学号：2023013549（个人

贡献度：45%）

软工2404班

王景涵同学 学号：2024013249

指导教师：王美丽（金博代）

日期：2026年9月9日