GSAG-CDGAN: A Generalizable Small-Sample Attention-Guided GAN for Remote Sensing Change Detection (Student Abstract)

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Abstract

Remote sensing change detection (RSCD) is crucial for urban monitoring, environmental protection, and disaster assessment, but small-sample scenarios often lead to overfitting and inaccurate predictions on unseen data. To address this, we propose GSAG-CDGAN, an end-to-end framework integrating Selective Noise Augmentation (SNA) to mitigate overfitting, an Attention-Guided Adversarial Network (AGAN) to enhance structural consistency, and a Perceptual Loss Module (PLM) to preserve semantic consistency. Experiments on CDData-50 show that GSAG-CDGAN improves F1-Score from 0.6954 to 0.8851, with notable gains in Recall and IoU, demonstrating enhanced robustness under small-sample conditions. Further evaluation on the WHU-CD dataset yields an F1-Score of 0.9502, confirming strong cross-dataset generalization and the method's effectiveness in diverse scenarios.

Introduction

In recent years, remote sensing change detection (RSCD) has become an essential tool for extracting pixel-level changes from bi-temporal images, supporting applications such as urban monitoring, environmental protection, and disaster assessment. (Gui et al. 2024) In practice, however, RSCD models trained with limited annotated data frequently overfit, causing inaccurate predictions on unseen images and undermining real-world applicability.

To directly address this failure mode, our objective is to improve model generalization so as to reduce prediction errors on previously unseen data. Recent work on robust representation learning under data scarcity (Pei et al. 2025) provides useful insights that motivate our design of GSAG-CDGAN. Toward this end, we propose GSAG-CDGAN, an end-to-end framework specifically designed to enhance generalization in small-sample RSCD by countering overfitting and promoting robust performance across unseen distributions. GSAG-CDGAN integrates three complementary components: Selective Noise Augmentation (SNA), which increases training diversity by injecting targeted noise into unchanged regions to simulate real-world variations and mitigate overfitting; an Attention-Guided Adversarial Network (AGAN), which embeds spatial attention into both the generator and discriminator to strengthen structural consistency across temporal images while suppressing pseudo-changes; and a Perceptual Loss Module (PLM), which aligns high-level feature representations between predictions and ground truth to enforce semantic consistency and reduce reliance on dataset-specific artifacts. Together, these modules foster domain-invariant representations, making the learned decision criteria less dependent on spurious cues and thereby reducing prediction errors on previously unseen data in data-scarce scenarios.

Contributions. GSAG-CDGAN addresses overfitting in small-sample training by combining SNA, AGAN, and PLM to enhance structural and semantic consistency. Experiments on CDData-50 show substantial improvements in generalization and state-of-the-art performance.

Method

Overview

Remote sensing change detection (RSCD) under small-sample conditions often suffers from overfitting, leading to inaccurate predictions on unseen data. To improve generalization, we propose GSAG-CDGAN, an end-to-end framework with three complementary modules: Selective Noise Augmentation (SNA), Attention-Guided Adversarial Network (AGAN), and Perceptual Loss Module (PLM). As shown in Figure 1, SNA enriches training diversity, AGAN incorporates attention into adversarial learning to enforce structural consistency and suppress pseudo-changes, and PLM aligns high-level semantic representations to stabilize predictions. Together, these modules focus learning on robust change cues rather than dataset-specific artifacts, enhancing accuracy on unseen images.

Selective Noise Augmentation (SNA)

Overfitting in RSCD is largely driven by scarce annotated samples. To address this, SNA selectively injects noise into unchanged regions of bi-temporal images, producing diverse yet realistic training examples that preserve true change regions. By perturbing only background areas, SNA reduces reliance on incidental cues, encourages the network to learn discriminative structural differences, and improves generalization to unseen data, while enriching adversarial training and simulating realistic variability.

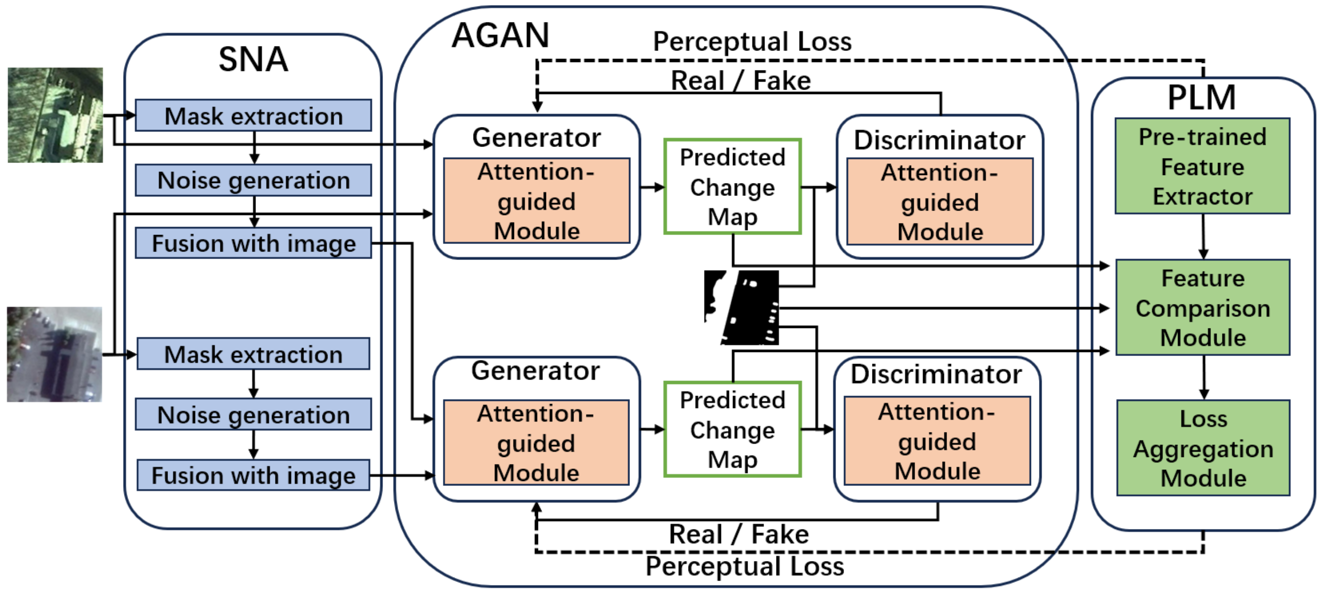

Figure 1: Framework of the proposed GSAG-CDGAN for remote sensing change detection, comprising SNA, AGAN, and PLM modules. box.

Attention-Guided Adversarial Network (AGAN)

Attention-Guided Adversarial Network (AGAN) is the adversarial backbone of GSAG-CDGAN, integrating attention into both generator and discriminator. In the generator, spatial-channel attention highlights true change regions and suppresses background noise, focusing on informative structures while filtering irrelevant textures and illumination, yielding more stable predictions. In the discriminator, attention emphasizes key regions and challenging boundaries, providing precise feedback that reduces dataset-specific artifacts. This dual-attention design mitigates overfitting in small-sample training, enhances structural consistency, and improves generalization and accuracy on unseen images.

Perceptual Loss Module (PLM)

Although adversarial training improves structural realism, overfitting can still cause inaccurate predictions on unseen data. To address this, the Perceptual Loss Module (PLM) aligns high-level feature representations between predicted and ground-truth change maps, encouraging preservation of semantic structures and class-discriminative cues. By reinforcing semantic consistency, PLM stabilizes training, mitigates reliance on dataset-specific artifacts, and enhances generalization to unseen samples when combined with SNA and AGAN.

Experiments

To evaluate GSAG-CDGAN's generalization under small-sample conditions, we conducted an ablation study on CDData-50 (50% of the original dataset) to simulate data-scarce scenarios. Starting from the SNUNet-CD(Fang et al. 2022) baseline, we progressively added Selective Noise Augmentation (SNA), Attention-Guided Adversarial Network (AGAN), and Perceptual Loss Module (PLM), improving F1-Score from 0.6954 to 0.8851, with notable gains in Recall and IoU (Table 1), demonstrating reduced overfitting and enhanced generalization.

Method	Precision	Recall	F1	OA	IoU
baseline	86.50	58.13	69.54	94.39	53.30
+ SNA	89.08	84.42	86.69	97.14	76.50
+ SNA + AGAN	89.20	86.85	88.24	97.30	78.22
GSAG-CDGAN	**89.62**	**87.40**	**88.51**	**97.45**	**78.65**

Table 1. Ablation study of GSAG-CDGAN components on CDData-50.

To further validate robustness and cross-dataset performance, GSAG-CDGAN was evaluated on the WHU-CD dataset, achieving an F1-Score of 0.9502, outperforming CGNet (0.9297)(Han et al. 2023) and C2F-SemiCD (0.9216)(Han et al. 2024), confirming its strong generalization across different scenarios.

Conclusion

We propose GSAG-CDGAN (SNA, AGAN, PLM) to enhance generalization in small-sample remote sensing change detection. The modules reduce reliance on dataset-specific artifacts, improve robust change learning, and stabilize predictions. Experiments show strong robustness and cross-dataset generalization. Future work includes testing on more datasets, developing lightweight/adaptive variants, integrating domain priors, exploring self-/semi-supervised learning, and extending the framework for large-scale applications.

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