How does the integration of CLIP-based alignment losses in latent diffusion models improve the semantic consis

Assignee Research

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Abstract

The interpretation of multi-temporal remote sensing imagery is critical for monitoring Earth's dynamic processes-yet previous change detection methods, which produce binary or semantic masks, fall short of providing human-readable insights into changes. Recent advances in Vision-Language Models (VLMs) have opened a new frontier by fusing visual and linguistic modalities, enabling spatio-temporal vision-language understanding: models that not only capture spatial and temporal dependencies to recognize changes but also provide a richer interactive semantic analysis of temporal images (e.g., gene

1 Introduction

This paper examines: Remote Sensing SpatioTemporal Vision-Language Models: A Comprehensive Survey. Research question: How does the integration of CLIP-based alignment losses in latent diffusion models improve the semantic consistency of generated aerial imagery compared to VAEs, as measured by ImageNet-VL accuracy?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.2/10.

3 Results

13 papers retrieved. 13 claims extracted; 0 independently verified. Quality review score: 3.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
R@K is calculated as TP@K / (TP@K + FN@K)	×	0.00
Precision@K (Pr@K) is calculated as TP@K / (TP@K + FP@K)	×	0.01
MIoU (Mean Intersection over Union) is calculated as the average of IoUk = |Pk $\cap$ Gk| / |Pk $\cup$ Gk| for K semantic classes	×	0.03
cIoU (cumulative Intersection over Union) is calculated as (Σ|Pi $\cap$ Gi|) / (Σ|Pi $\cup$ Gi|) for N samples	×	0.01
F1 score is the harmonic mean of Precision and Recall, calculated as 2 * TPk / (2 * TPk + FPk + FNk) for class k	×	0.03
LEVIR-CC dataset includes descriptions such as 'Two big roads have been built' and 'A couple of streets have been c'	×	0.02
SECOND-CC dataset includes the caption 'The green area and the playground at the edge of the stage are replaced with bui	×	0.01
LEVIR-MCI dataset includes the caption 'The sparse vegetation is replaced by some roads and large constructions with par	×	0.07
PromptCC (Liu et al.) and KCFI (Yang et al.) are examples of Prompt Tuning methods	×	0.01
Change-Agent (Liu et al.) and RSChatgpt (Guo et al.) are examples of Unified Data Representation methods	×	0.07
Remote sensing change detection (CD) aims to identify differences between images acquired at different time points	×	0.11
Binary CD focuses on locating areas of change at the pixel level without providing semantic insights	×	0.07
Semantic CD extends binary methods by labeling each changed region	×	0.03

References

- http://arxiv.org/abs/2302.08510v2

- http://arxiv.org/abs/2508.11919v3
- http://arxiv.org/abs/2412.02573v3