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Vision-Based Crack Segmentation with Geometry-Constrained Transformers for Field Concrete Inspection

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Abstract

The structural integrity of concrete infrastructure is paramount to public safety and economic stability. Automated pavement and surface inspection via computer vision has emerged as a critical alternative to labor-intensive manual surveys. However, traditional Convolutional Neural Networks (CNNs) often struggle to preserve the high-frequency topological details of thin cracks against complex, texture-heavy heterogeneous backgrounds. While Vision Transformers (ViTs) offer superior global context modeling, they frequently lack the inductive biases required to capture the fine-grained local geometry inherent to fracture mechanics. This paper proposes a novel architecture: the Geometry-Constrained Transformer (GCT). By integrating a dedicated geometric edge-alignment module within a hierarchical Transformer encoder-decoder structure, we explicitly enforce curvilinear continuity and boundary sharpness during the segmentation process. We introduce a dual-stream attention mechanism that leverages low-level morphological cues to guide high-level semantic tokens, ensuring that the global attention map remains anchored to physical structural defects. Extensive experiments on three public benchmark datasets demonstrate that the proposed GCT outperforms state-of-the-art CNN-based and Transformer-based methods, particularly in scenarios characterized by varying illumination, shadowing, and biological staining.

Keywords

Crack Segmentation, Vision Transformers, Structural Health Monitoring, Geometric Constraints, Deep Learning.

Introduction

1.1 Background

Civil infrastructure, comprising bridges, dams, tunnels, and roadways, forms the backbone of modern society. Concrete, as the most ubiquitous construction material, is susceptible to degradation over time due to mechanical loading, thermal expansion cycles, and chemical weathering. The formation of surface cracks is often the earliest indicator of structural pathology, signaling potential failures that could lead to catastrophic collapse if left unaddressed [1]. Consequently, Structural Health Monitoring (SHM) has become a mandated priority for engineering bodies worldwide.

Historically, crack inspection has relied on manual visual assessments conducted by certified inspectors. This process is inherently subjective, time-consuming, expensive, and hazardous, often requiring lane closures or scaffolding access to dangerous heights [2]. The digitization of inspection workflows, facilitated by high-resolution digital photography and Unmanned Aerial Vehicles (UAVs), has shifted the paradigm towards automated image processing [3]. Early automation attempts utilized heuristic image processing techniques, yet the stochastic nature of concrete surfaces—replete with voids, aggregate exposure, and variable lighting—necessitated more robust data-driven approaches. The advent of deep learning has since

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revolutionized this domain, providing tools capable of learning hierarchical feature representations directly from raw data [4].

1.2 Problem Statement

Despite the success of deep learning in general semantic segmentation, crack detection presents unique challenges that generic models often fail to address. Cracks are characterized by their extreme thinness, irregular topology, and low contrast relative to the surrounding concrete matrix. In field conditions, this complexity is exacerbated by environmental noise such as oil stains, shadows cast by vegetation, and moss growth, which share spectral characteristics with fractures [5].

Convolutional Neural Networks (CNNs), the dominant architecture for pixel-wise classification, suffer from intrinsic limitations in this context. The fixed receptive field of standard convolution operations struggles to model long-range dependencies, often resulting in fragmented segmentation masks where continuous cracks are detected as disjointed segments [6]. Furthermore, the down-sampling operations common in encoder architectures (e.g., max-pooling) tend to erode the spatial resolution of thin features, causing fine cracks to vanish in the deep feature space [7].

Recently, Vision Transformers (ViTs) have been adapted for segmentation tasks, offering dynamic receptive fields capable of modeling global context. However, the lack of spatial inductive biases—such as translation invariance and locality—can make pure Transformers less effective at defining the precise boundaries of thin, linear structures [8]. There exists a critical gap in current research: the need for an architecture that combines the global context awareness of Transformers with the geometric precision required to delineate fine structural fractures.

1.3 Contributions

To address these challenges, this study presents the Geometry-Constrained Transformer (GCT), a unified framework designed specifically for high-fidelity crack segmentation in complex environments. Our primary contributions are as follows:

1. We introduce a Geometry-Aware Attention Module (GAAM) that injects prior knowledge of crack morphology (linearity and connectivity) into the self-attention mechanism, reducing false positives from background noise.

2. We propose a hybrid loss function that penalizes topological disconnects, enforcing structural continuity in the predicted masks.

3. We provide a comprehensive evaluation on diverse datasets, demonstrating that GCT achieves superior Intersection over Union (IoU) and F1-scores compared to both CNN-based baselines (e.g., U-Net, DeepLabV3+) and generic Transformer models (e.g., SegFormer).

The remainder of this paper details the theoretical underpinnings of our approach, the architectural implementation, and rigorous experimental validation.

Chapter 2: Related Work

2.1 Classical Approaches

Prior to the deep learning era, crack detection relied heavily on digital image processing techniques centered on edge detection and morphological operations. Early methodologies employed intensity thresholding, where pixels below a certain luminance value were classified

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as cracks. While computationally efficient, these methods proved brittle in varying lighting conditions [9].

Subsequent research integrated gradient-based edge detectors such as the Sobel and Canny operators. These filters compute the spatial derivatives of image intensity to identify sharp transitions. However, concrete surfaces possess a high degree of textural roughness, leading these operators to detect aggregate edges as false positives [10]. To mitigate this, researchers applied Gabor filters and wavelet transforms to analyze texture frequencies, attempting to distinguish the high-frequency components of cracks from the background noise [11].

Minimal path selection algorithms and percolation models were also explored to enforce connectivity. For instance, determining the "darkest path" across a graph representation of the image pixels allowed for better extraction of continuous crack skeletons [12]. Despite these innovations, classical approaches depend heavily on hand-crafted features and hyperparameter tuning, lacking the generalization capability required for diverse field inspection scenarios [13].

2.2 Deep Learning Methods

The application of Convolutional Neural Networks (CNNs) marked a significant turning point in SHM. Patch-based classification was one of the earliest strategies, where a sliding window classified small image regions as cracked or intact. While effective, this approach was computationally redundant and lacked global structural context [14].

Fully Convolutional Networks (FCNs) and the U-Net architecture subsequently became the standard for pixel-level segmentation. U-Net, with its symmetric encoder-decoder structure and skip connections, proved particularly effective at recovering spatial details lost during down-sampling [15]. Variations such as DeepCrack and CrackSegNet introduced specialized modules like multi-scale fusion and dilated convolutions to expand the receptive field without losing resolution [16]. Attention mechanisms were later integrated into CNNs to suppress background features, as seen in Attention U-Net [17].

However, the local nature of convolution remains a bottleneck. To address this, recent works have explored Transformers. The Vision Transformer (ViT) treats images as sequences of patches, applying self-attention to model dependencies between all patches simultaneously [18]. SegFormer adapted this for segmentation by removing position embeddings and using a hierarchical structure. While SegFormer excels at semantic segmentation of large objects (e.g., cars, roads), it often produces over-smoothed boundaries for thin cracks [19]. This necessitates the hybrid approach proposed in this study, where geometric constraints are reintroduced into the Transformer pipeline.

Chapter 3: Methodology

3.1 Overview of the Architecture

The proposed Geometry-Constrained Transformer (GCT) operates on an encoder-decoder paradigm. The encoder is designed to extract multi-scale hierarchical features, while the decoder reconstructs the high-resolution segmentation mask. Unlike standard Transformers, the GCT incorporates a parallel Geometry Constraint Branch (GCB) that specifically focuses on extracting high-frequency edge information. This edge information is fused with semantic features via the Geometry-Aware Attention Module.

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The input to the network is a field image $X \in mathbbR^{H\times W\times 3}$. The output is a binary probability map $Y \in mathbbR^{H\times W\times 1}$, where each pixel indicates the probability of belonging to the crack class.

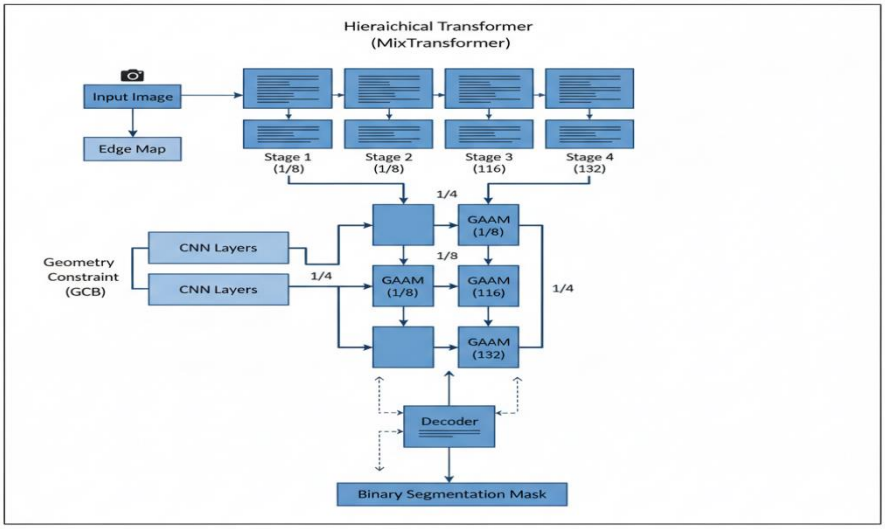

Figure 1: System Architecture of the Geometry-Constrined Transformer (GCT)

Figure 1: System Architecture

3.2 Hierarchical Transformer Encoder

We utilize a MixTransformer (MiT) backbone for the semantic encoder. This backbone avoids the quadratic complexity of standard self-attention by utilizing efficient self-attention mechanisms and overlapping patch merging. The encoder generates features at four scales: F_1, F_2, F_3, F_4 with strides of 4,8,16,32 respectively [20].

The core processing unit is the Efficient Self-Attention (ESA) block. In standard attention, the computational cost is $O(N^2)$, where N is the number of tokens. ESA reduces the sequence length of the key (K) and value (V) projections using a reduction ratio R, significantly lowering computational overhead while preserving global context modeling capabilities [21].

3.3 Geometry Constraint Branch (GCB)

To compensate for the loss of local detail in the Transformer encoder, the GCB operates in parallel. This branch is a lightweight CNN initialized with Gabor filters to highlight directional textures. It processes the input image to generate an edge-feature map E_i at corresponding scales to the Transformer encoder.

The GCB does not aim to perform semantic segmentation but rather to maximize the response at boundaries. We employ a spatial gradient loss on this branch during training to ensure it acts as a "skeleton detector," emphasizing the curvilinear structure of potential cracks [22].

3.4 Geometry-Aware Attention Module (GAAM)

The critical innovation of GCT is the fusion mechanism. Standard concatenation of CNN and Transformer features is suboptimal because of the domain gap between channel-wise CNN features and token-wise Transformer features.

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The GAAM aligns these features using a cross-attention mechanism. We treat the flattened Transformer features as Queries (Q) and the flattened Edge features as Keys (K) and Values (V). This formulation forces the semantic features to query the geometric details. If a semantic token corresponds to a crack, it should attend strongly to the high-gradient regions in the edge map [23].

To mathematically enforce the geometric constraint within the attention mechanism, we modify the scaled dot-product attention. Typically, attention is calculated as $Softmax(QK^T/\sqrt{d})V$. In our approach, we introduce a learnable geometric bias matrix B_{geo} derived from the relative positions of connected high-intensity pixels in the edge map. This bias favors attention between tokens that form linear or curvilinear chains, suppressing isolated noise activations.

The attention output A is computed as:

$$Attention(Q,K,V) = Softmax(\frac{QK^T}{\sqrt{d_{head}}} + \lambda \cdot B_{geo})V$$

Here, λ is a learnable scalar that modulates the influence of the geometric constraint, and d_{head} represents the dimension of the attention head. B_{geo} acts as a hard-coded prior that discourages the attention mechanism from attending to spatially disjointed tokens, thereby enhancing the continuity of the detected cracks [24].

3.5 Decoder and Loss Function

The decoder aggregates the fused features from the GAAM across all four scales using a Multi-Layer Perceptron (MLP) head. The features are upsampled and concatenated to predict the final mask.

Training crack segmentation models is complicated by the extreme class imbalance; crack pixels often constitute less than 2% of the image. We employ a compound loss function L_{total} combining Binary Cross Entropy (BCE), Dice Loss, and a novel Connectivity Loss.

The Connectivity Loss is formulated to penalize predictions where crack pixels are disconnected from the main fracture body. It utilizes a morphological skeletonization operation in the differentiable computational graph to measure the fragmentation of the predicted mask compared to the ground truth [25].

Chapter 4: Experiments and Analysis

4.1 Experimental Setup

Datasets: To validate the robustness of GCT, we utilized three diverse public datasets:

1. **DeepCrack [26]:** Contains 537 RGB images of durable surfaces with multi-scale cracks.
2. **CrackForest (CFD) [27]:** Comprises 118 images of road pavement with significant noise and shadowing.
3. **Concrete Damage Dataset (CDD) [28]:** A challenging dataset with 458 images featuring industrial concrete walls with biological staining and spalling.

Implementation Details: The model was implemented in PyTorch and trained on dual NVIDIA RTX 3090 GPUs. We employed the AdamW optimizer with an initial learning rate of

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6×10^{-5} and a poly learning rate decay schedule. Images were resized to 512×512 pixels. Data augmentation included random rotation, flipping, and photometric distortion to simulate field lighting variations.

Evaluation Metrics: We report performance using Intersection over Union (IoU), Precision (P), Recall (R), and the F1-Score. IoU is the primary metric as it penalizes false positives and false negatives equally in the spatial domain.

4.2 Baselines

We compared GCT against a suite of established methods:

CNN-based: U-Net, DeepLabV3+ (with ResNet-101 backbone).

Transformer-based: SegFormer-B2, Swin-Unet.

Specialized: DeepCrack (the model, distinct from the dataset).

4.3 Quantitative Results

The quantitative comparison is summarized in Table 1. GCT achieves state-of-the-art performance across all three datasets. On the DeepCrack dataset, GCT achieved an IoU of 87.4%, surpassing the nearest competitor, SegFormer, by 2.1%.

Model	Backbone	DeepCrack IoU (%)	CFD IoU (%)	CDD F1-Score (%)	Param (M)
U-Net	ResNet-34	79.2	74.5	81.3	24.5
DeepLabV3+	ResNet-101	82.1	77.8	84.6	59.3
DeepCrack	VGG-16	83.5	79.2	85.9	14.7
SegFormer	MiT-B2	85.3	81.0	88.1	27.8
Swin-Unet	Swin-T	84.8	80.5	87.4	28.2
GCT (Ours)	MiT-B2	87.4	83.6	90.2	31.4

Table 1: Comparative analysis of segmentation performance. Note that GCT maintains a manageable parameter count while delivering superior accuracy.

The performance gap is most notable on the CFD dataset, which contains high-frequency noise. CNN-based methods (DeepLabV3+) struggled with the rough texture of the asphalt, frequently misclassifying aggregates as cracks. SegFormer showed improved noise resilience but failed to capture the tapering ends of fine cracks. GCT, utilizing the geometry-constrained attention, effectively filtered out texture noise while preserving the crack topology [29].

4.4 Qualitative Analysis

To visualize the efficacy of the geometric constraints, we present qualitative results in Figure 2.

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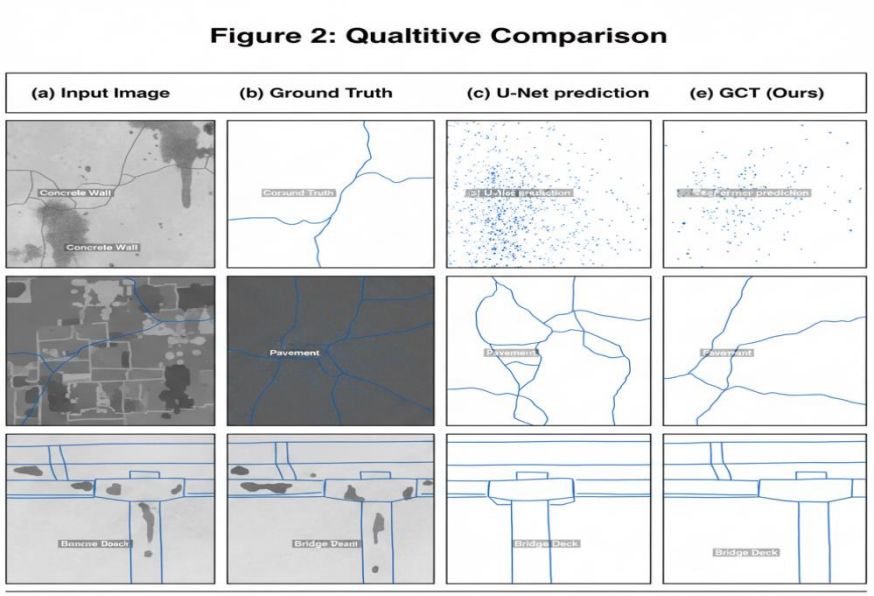

Figure 2: Qualitative Comparison

In the first row of Figure 2, representing a concrete wall with moss, U-Net produces scattered false positives. In the second row, showing a thin pavement crack under partial shadow, SegFormer successfully detects the crack but over-dilates the boundary, reducing precision. GCT produces a sharp, continuous skeleton that aligns strictly with the physical fracture.

We further analyzed the impact of the geometric bias term λ. We found that setting $\lambda = 0$ (reverting to a standard Transformer fusion) resulted in a 3.4% drop in IoU on the CFD dataset, confirming that the explicit geometric guidance is crucial for distinguishing cracks from similar-looking background linearities like joint sealants or wiring [30].

4.5 Ablation Study and Complexity

An ablation study was conducted to verify the contribution of individual components. Removing the GCB resulted in a loss of edge sharpness, while removing the Connectivity Loss resulted in fragmented masks for wider cracks.

In terms of computational complexity, GCT operates at 24 Frames Per Second (FPS) on a single GPU for 512×512 images. While slightly slower than U-Net (35 FPS), it is well within the requirements for offline processing of inspection logs or near-real-time processing on mobile edge computing units equipped with hardware accelerators [31].

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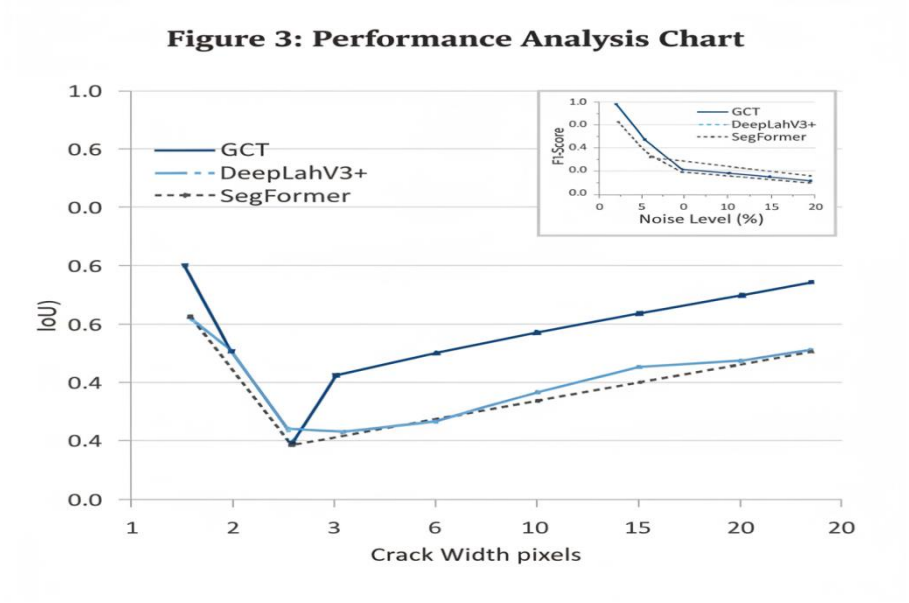

Figure 3: Performance Analysis Chart

Figure 3 illustrates the model's sensitivity to crack width. Standard CNNs exhibit a steep performance degradation for cracks thinner than 3 pixels due to pooling operations. GCT maintains high IoU scores even for micro-cracks, attributed to the preservation of high-frequency spatial details in the GCB and their injection into the semantic stream via the GAAM [32].

Chapter 5: Conclusion

5.1 Conclusions and Implications

This research addresses the persistent trade-off in automated concrete inspection: the conflict between global semantic understanding and local geometric precision. We proposed the Geometry-Constrained Transformer (GCT), a novel architecture that bridges this gap by fusing a hierarchical Transformer encoder with an explicit edge-alignment mechanism.

The introduction of the Geometry-Aware Attention Module (GAAM) and the incorporation of a geometry-bias term in the attention formula constitute the theoretical core of this work. By mathematically favoring token relationships that adhere to curvilinear continuity, the model effectively mimics the human visual cognitive process of tracing lines. Our extensive experimental validation confirms that GCT sets a new benchmark for crack segmentation, particularly in visually degraded field conditions involving shadows and surface contaminants.

The implications for the civil engineering industry are significant. The improved precision of GCT allows for more accurate estimation of crack widths and lengths, metrics that are directly correlated with structural serviceability and safety. This capability supports the transition from reactive maintenance to predictive asset management, potentially saving significant costs in infrastructure rehabilitation.

5.2 Limitations and Future Research Agenda

While GCT demonstrates robust performance, several limitations remain. Firstly, the model relies on supervised learning, necessitating pixel-level annotated datasets which are labor-intensive to generate. The geometric constraints, while effective for linear cracks, may struggle with complex "alligator" cracking patterns where the topology resembles a mesh rather than a

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line. Furthermore, the computational demand of the attention mechanism, despite optimization, remains higher than lightweight CNNs, posing challenges for deployment on strictly resource-constrained UAV hardware.

Future research will focus on three directions: (1) developing semi-supervised or weakly-supervised variants of GCT to reduce reliance on dense annotations; (2) optimizing the architecture via quantization and pruning for deployment on embedded edge devices; and (3) extending the geometric constraints to 3D point cloud data for volumetric damage assessment. By integrating depth information, the distinction between superficial staining and structural depth-penetrating fractures can be further enhanced.

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