

Trainable Topology Supervision under Structurally Unreliable Pseudo Supervision

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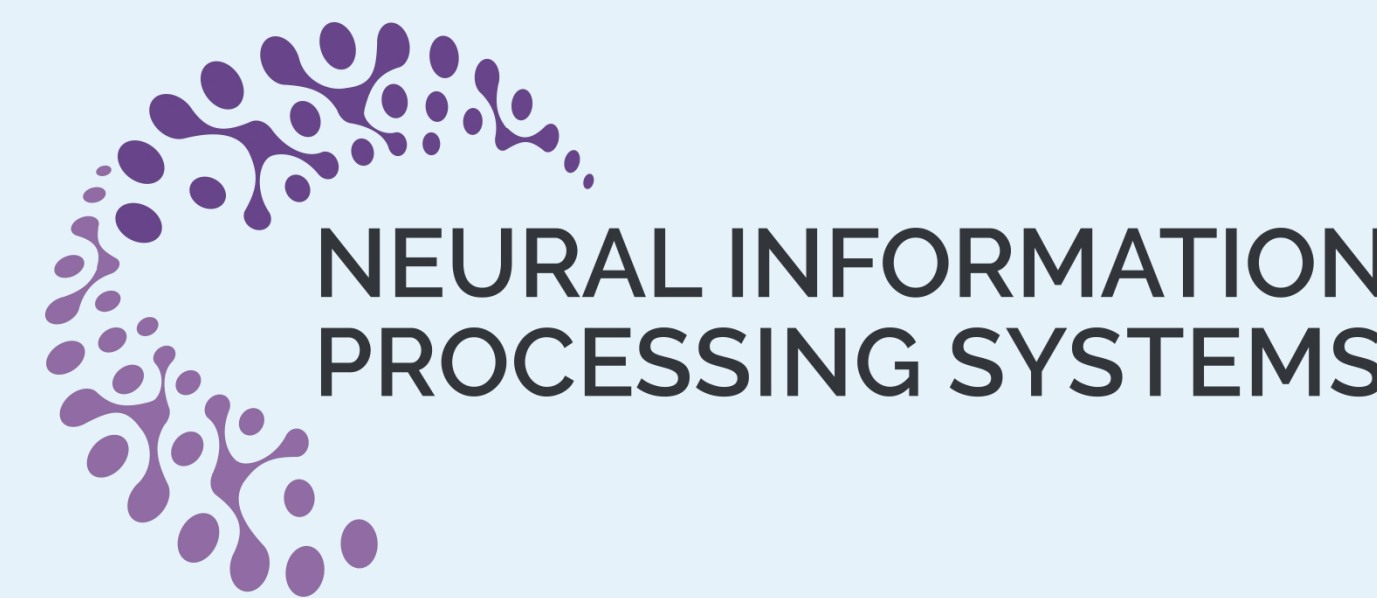
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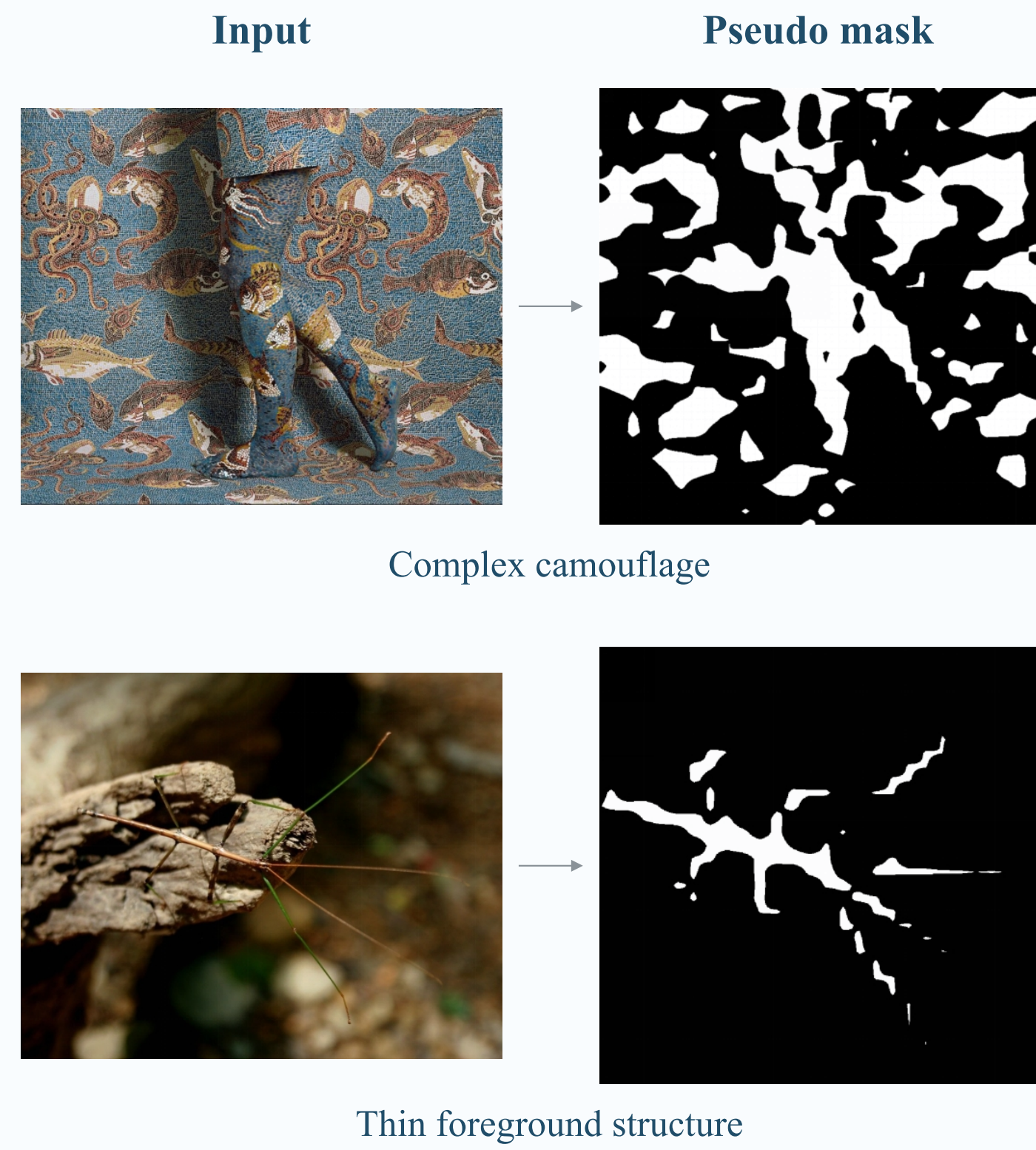
Directly fitting unreliable pseudo topology can reinforce structural errors. Our Method derives trainable proxy signals and injects them conservatively.

01 · Motivation

Structural Unreliability

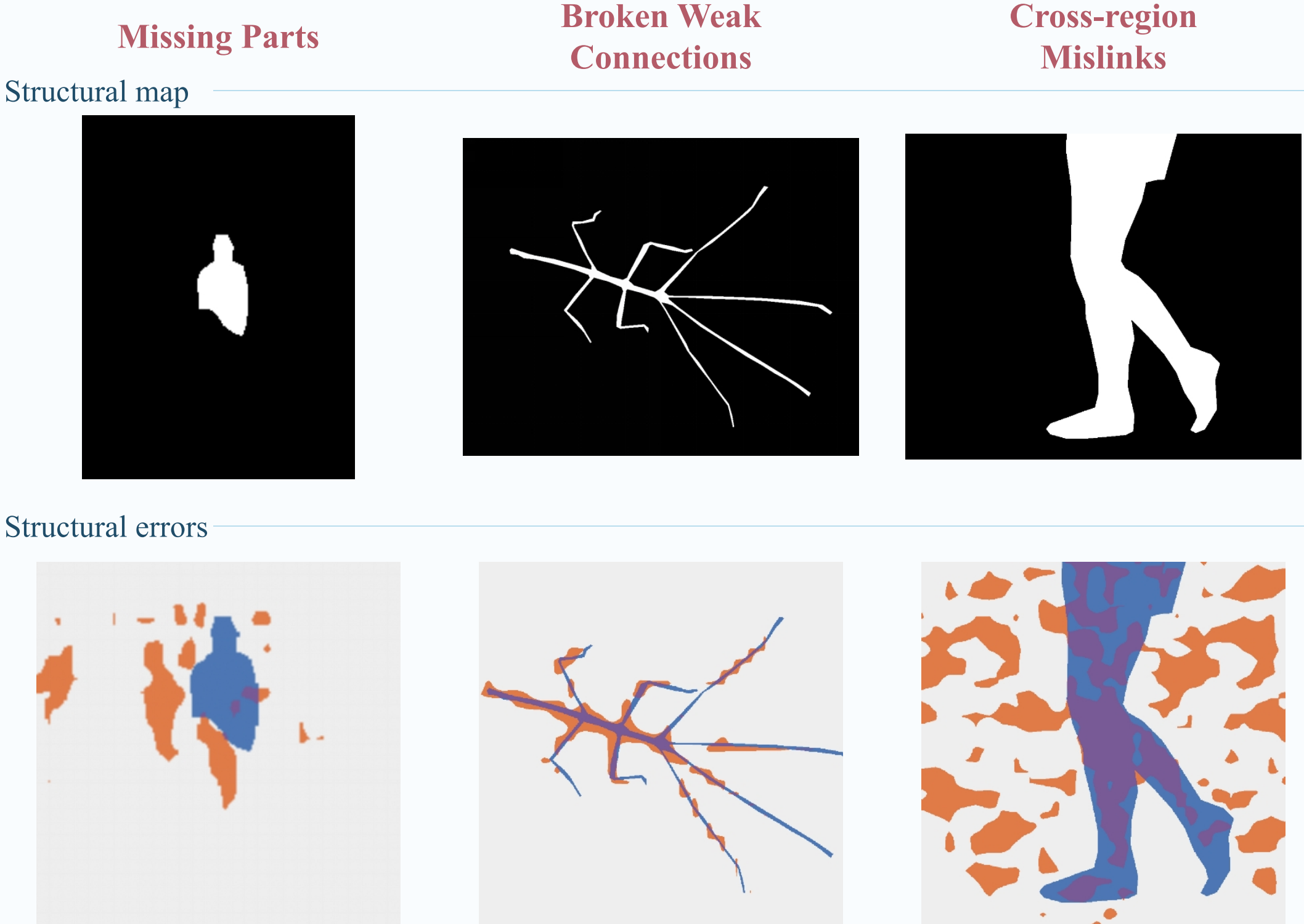
Observed Pseudo Supervision

Fig. 1(a) · observed pairs



Typical Structural Distortions

Fig. 1(c) · independent schematic examples



Local pseudo-mask errors can alter connectivity and structural correspondence.

Premise Shift

Conventional Premise

When the reference topology is reliable, direct structural matching is meaningful.

Unreliable Pseudo Supervision

Matching distorted pseudo topology may reinforce the errors it encodes.

Research Questions

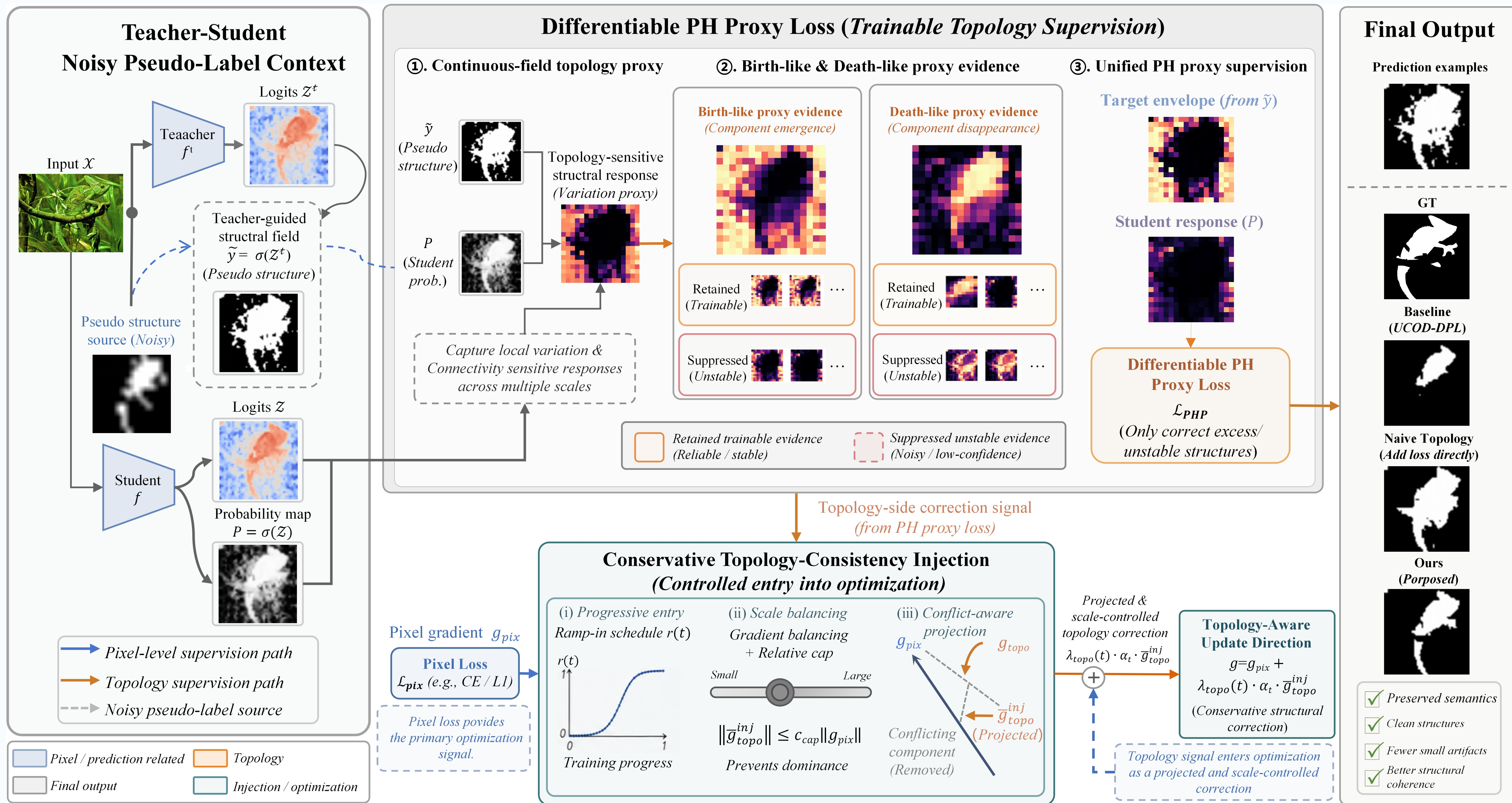
Q1 · Trainable Signals

Which topology variations can guide learning without treating the pseudo structure as an exact target?

Q2 · Conservative Optimization

How should topology corrections enter student optimization without destabilizing the main objective?

02 · Our Method Framework



03 · Quantitative Evaluation

UCOD-DPL · DINOv2 · Four-benchmark Mean · No topology → Ours

Weighted F-measure ↑

+3.85%

0.683 → 0.710

β₀ Counting Error ↓

−23.72%

8.837 → 6.741

β₁ Counting Error ↓

−36.32%

4.785 → 3.047

Same-carrier Topology Comparison · Table 2

Method	F _F ↑	β ₀ Error ↓	β ₁ Error ↓
No topology	0.683	8.837	4.785
TopoLoss	0.310	19.238	8.366
TopoSemiSeg	0.552	5.323	2.150
SATLoss	0.479	5.342	2.241
MATCH	0.521	5.290	2.489
Ours	0.710	6.741	3.047

Lower Betti-counting errors do not necessarily imply better segmentation quality.

Mechanism Validation · NC4K

PH Proxy Formulation · Table 4

Mode	MAE ↓	F _F ↑	β ₀ ↓	β ₁ ↓
Match	0.056	0.720	2.495	2.173
Simplicity	0.060	0.708	3.465	2.222
Cap	0.051	0.741	3.591	2.286

Cap improves MAE and weighted F-measure over Match, with higher β₀ and β₁ counting errors.

Cross-setting Validation

Matched Histology · Dice ↑ · Table 7

CRAG	0.765 → 0.775
GlaS	0.815 → 0.835
MoNuSeg	0.299 → 0.310

No topology → Ours · Matched histology segmentation

Cross-backbone Controlled Comparison

Backbone	No Topology	Ours	Relative Change
DINOv1	0.634	0.660	+4.14%
DINOv2	0.683	0.710	+3.85%

Table 1 · Weighted F-measure

MAE ↓: DINOv1 0.077 → 0.070

DINOv2 0.061 → 0.055

Conservative Injection · Table 3

Mode	MAE ↓	F _F ↑	β ₀ ↓	β ₁ ↓
No topology	0.059	0.713	5.577	3.261
Direct PH addition	0.150	0.496	5.797	3.027
Sum-level	0.052	0.739	3.758	2.477
Per-term	0.051	0.741	3.591	2.286

Direct PH addition reduces weighted F-measure: 0.713 → 0.496.

Conservative injection: 0.739–0.741.

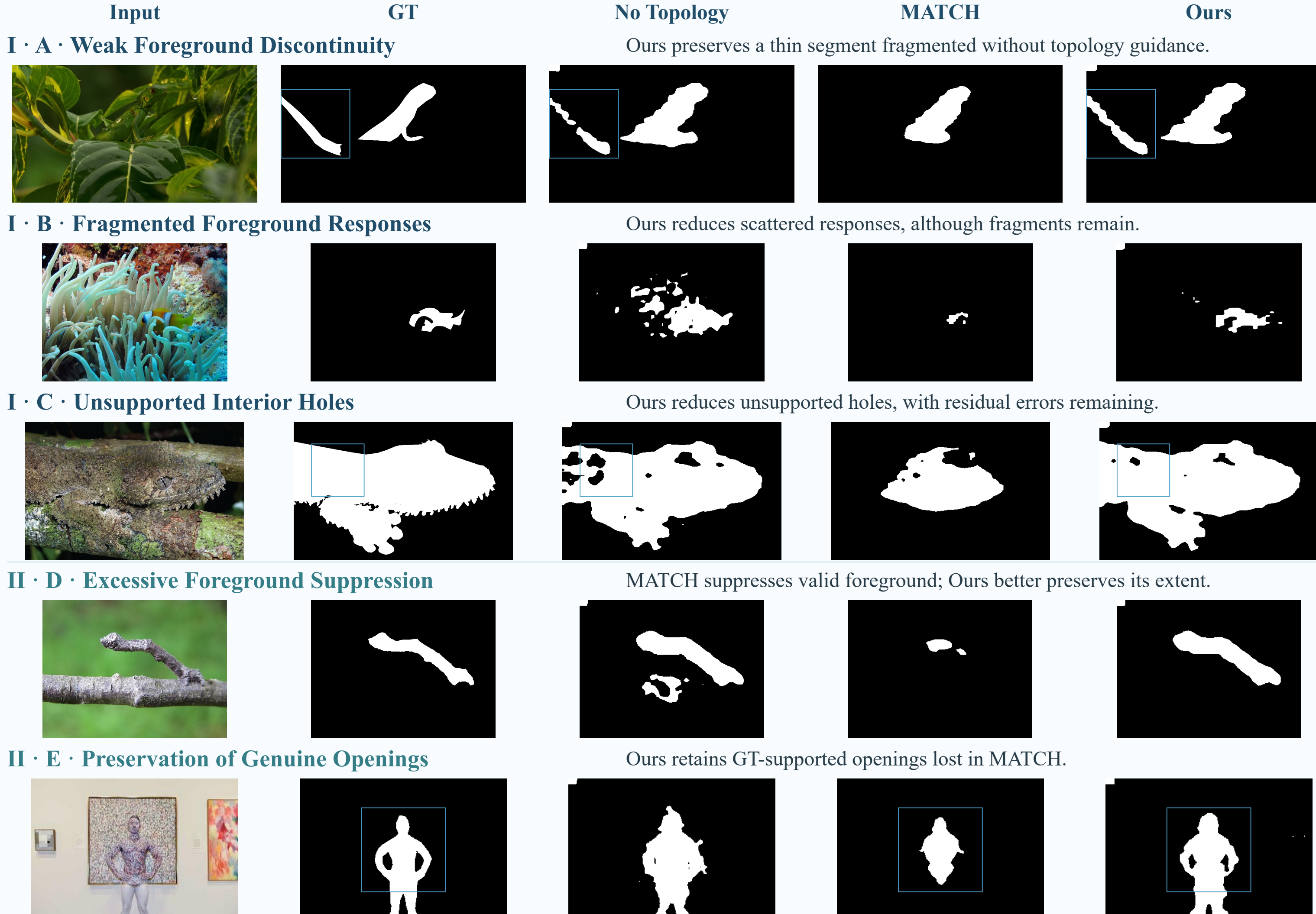
Controlled Structural Corruption · Table 12

Weighted F-measure ↑	0.744 → 0.753
MAE ↓	0.055 → 0.051
BME ↓	8.298 → 8.117

NC4K · Mean over Breaks / Holes / Merges / Blobs

04 · Qualitative Results

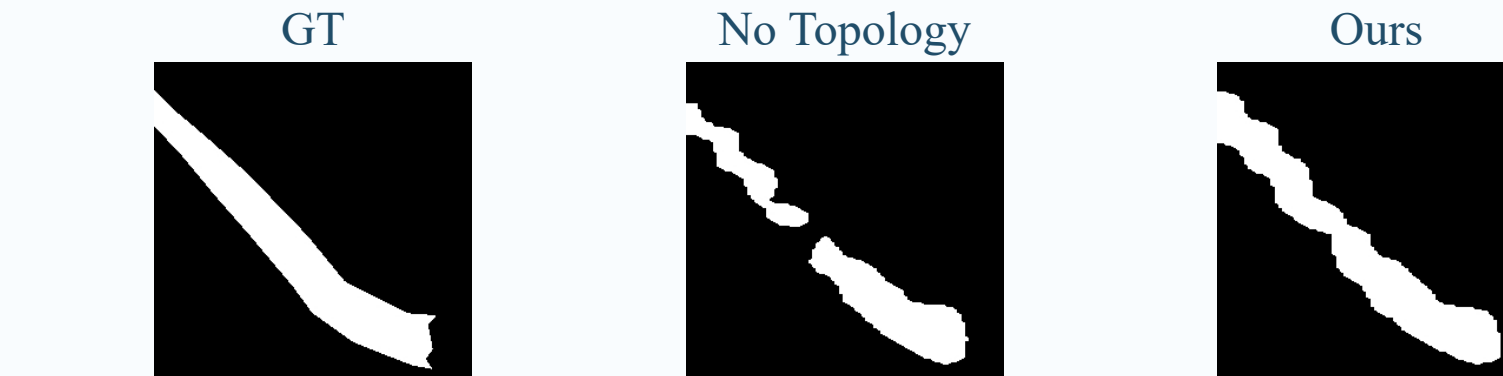
Rows I (A–C): Mitigating Structural Artifacts · Rows II (D–E): Preserving Valid Structures



05 · Structural Analysis

Structural Diagnostics · Crop-local Evidence

A · Weak Connectivity



Ours retains local continuity.

C · Spurious Holes



Unsupported holes decrease; residual errors remain.

E · Genuine Openings



Ours preserves openings lost in MATCH.

Scope and Limitations

Validated on UCOD and matched histology; broader settings remain untested.

Extremely weak or fragmented foreground evidence limits complete recovery.

Local analytical properties do not establish global training guarantees.