Enhancing topology properties in neural networks for better closed-shape extraction of historical maps

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September 2022

SoDuCo: **So**cial **Du**namics in **U**rban **Co**ntext

Project funded by the French national research agency (ANR)

Goal: Better understand **Urban Dynamics** applied to **Paris** city 1789-1950
Context: Both **historical maps** and **directories**
Main-task: Study **spatial-temporal information** in different map series.
In this presentation: Instance segmentation of historical maps.

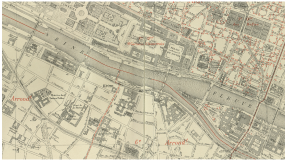
`https://anr.fr/Projet-ANR-18-CE38-0013`

Introduction and problem statement

Original image dataset: A set of 24 atlases (around 20 sheets) from 1866 to 1937

Atlas municipal des vingt arrondissements de Paris. 1925. Bibliothèque de l'Hôtel de Ville. Ville de Paris.

`http://bibliotheques-specialisees.paris.fr/ark:/73873/pf0000935524`



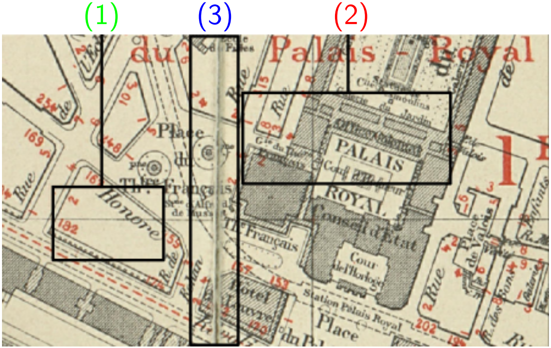
(a) Image

(b) Semantic segmentation

(c) Instance segmentation

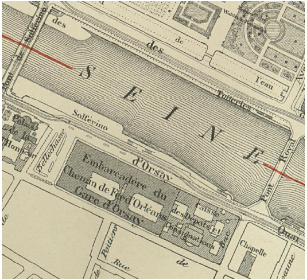
(d) Panoptic segmentation

Our goal: Instance segmentation
Long term goal: Panoptic segmentation

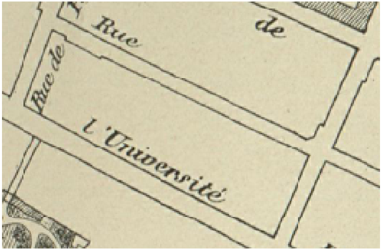


Challenges in theses historical maps atlases atlas series:
(1) planimetric overlap,
(2) text overlap,
(3) paper folds.

Introduction and problem statement
Texture information is not the key information to separate objects



Textural objects, rivers & buildings (Textured based classification)

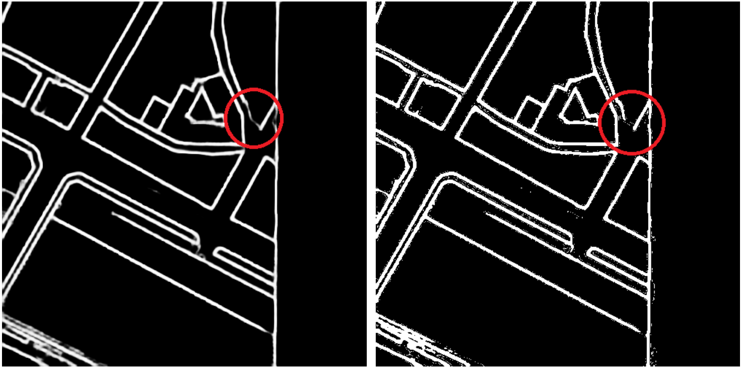


Non textural objects, Building blocks and roads (Shape based classification)

Conclusion: The objects can not be only classify by **textures** but with **shapes**. We proposed to extract boundary of objects to minimize the effect of texture and shapes.

Proposed method

Failure case extracting shapes through deep edge detector



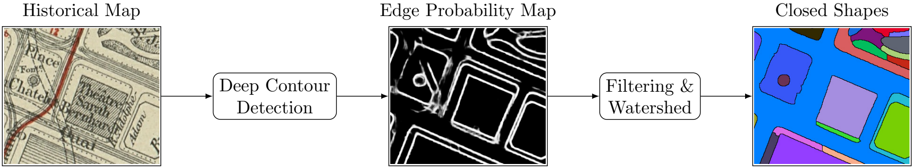
(a) Edge probability map (value from 0 to 1)

(b) Binary image (Threshold > 0.5)

Connected component extraction (**CC labelling**): Threshold the edge probability map and running connected component analysis to get components from the images.

Proposed method

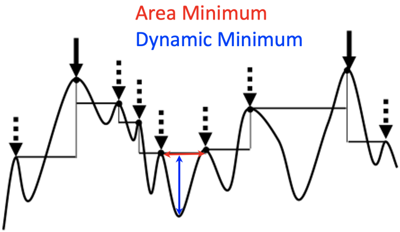
Proposed pipeline to extract closed shapes



Our proposed pipeline

Proposed method

Watershed segmentation have problem of over-segmentations



Pre-filtering with **Area minimum** and **Dynamic minimum**

Watershed segmentation (Weak edges recovery):
Area minimum filtering : *100px-900px*
Dynamic minimum filtering : *0-10*
Meyer watershed propagation

Evaluation protocol & Results

Original image and predicted EPM map

(a) Map image input

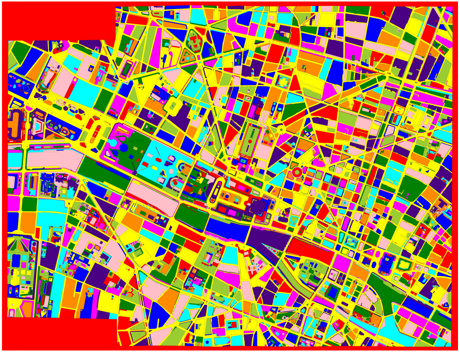
(b) Edge probability map

Left image: The input original map images
Right image: The predicted edge probability map from BDCN network

Atlas municipal des vingt arrondissements de Paris. 1925. Bibliothèque de l'Hôtel de Ville. Ville de Paris.

http://bibliotheques-specialisees.paris.fr/ark:/73873/pf0000935524

(c) Edge probability map



(d) Map instances

Left image: The predicted edge probability map from BDCN network

Right image: Instance map created by watershed algorithm which use edge probability map as input

Evaluation protocol & Results

COCO panoptic evaluation methods

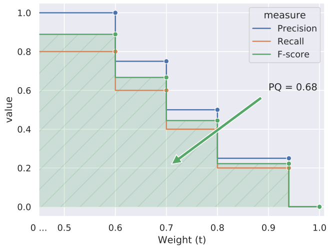
1. SQ = Segmentation Quality
2. RQ = Detection Quality
3. PQ = Panoptic Quality

$$PQ = \frac{\sum_{(t_i,p_j)\in TP} IoU(t_i,p_j)}{|TP| + \frac{1}{2}|FP| + \frac{1}{2}|FN|}, \tag{1}$$

$$SQ = \frac{\sum_{(t_i,p_j)\in TP} IoU(t_i,p_j)}{|TP|}, \quad RQ = \frac{|TP|}{|TP| + \frac{1}{2}|FP| + \frac{1}{2}|FN|}. \tag{2}$$

$$PQ = RQ \times SQ \tag{3}$$

Kirillov, A., He, K., Girshick, R., Rother, C., & Dollár, P. (2019). Panoptic segmentation.



	CC-labeling			Watersheding		
COCO	PQ	SQ	RQ	PQ	SQ	RQ
(%)	0.21	0.77	0.27	0.52	0.88	0.59

Evaluation metrics without watershed (CC-labeling) and watershed.
CC-labelling: Binarize and label the connected components of edge probability map.
PQ ($SQ \times RQ$), SQ (segmentation) and RQ (retrieval) are COCO Panoptic global metrics for each system.

Our proposed baseline methods
Strength and weakness

Deep edge detector strength:

1. Good performance of filtering edges

Watershed strength:

1. Closed shape extraction with topology guarantee
2. Thin boundary (1 pixel length)->slightly improve our evaluation scores

Deep edge detector weakness:

1. Create broken edges
2. Create weak edges
3. Not guarantee of closed shapes

Watershed weakness:

1. Noise sensitive (leads to over-segmentation)
2. Cannot recover disappear boundary (boundary value is 0)

Research Question

How to:

- Prevent broken/weak edges in EPM (benefit for watershed segmentation approach)
- Minimize the noise in the background (solving over-segmentation problem of watershed)

for better closed-shape extraction through our proposed pipeline?

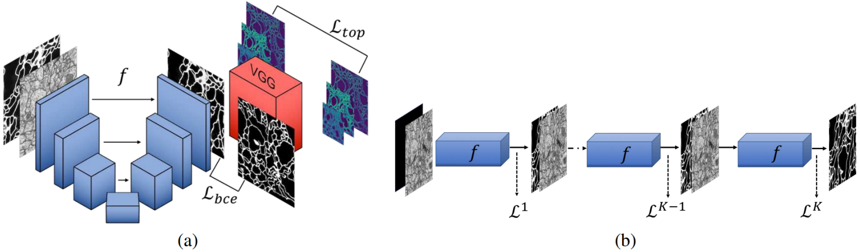
We are answering the research question in three research directions:

- Networks architecture
- Boundary of objects
- Through Critical points in the manifold of likelihood

Enhancing topology of edge image through networks architectures

U-Net+VGG

1. A iterative process for edge refinement process
2. VGG network is used to measure the topology difference between the prediction and ground truth EPM



Pipeline of U-Net+VGG architecture

Mosinska, A., Marquez-Neila, P., Koziński, M., Fua, P. (2018). Beyond the pixel-wise loss for topology-aware delineation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3136-3145).

Enhancing topology of edge image through networks architectures

U-Net+VGG

Total loss function:

$$L(x,y,w) = L_{bce}(x,y,w) + \mu L_{unetvgg}(x,y,w) \tag{4}$$

Binary cross entropy loss:

$$L_{bce}(x,y,w) = -\sum_{i}(1-y_i)\cdot\log(1-f_i(x,w)) + y_i\cdot\log f_i(x,w) \tag{5}$$

VGG-topology loss (Average mean square error):

$$L_{unetvgg}(x,y,w) = -\sum_{n=i}^{N}\frac{1}{M_n * W_n * H_n}\sum_{m=1}^{M_n}||I_n^m - I_n^m(f(x,w))||_2^2 \tag{6}$$

I_n^m: m feature map in the n^{th} layer; W_n, H_n: width and height in n^{th} layer

Enhancing topology of edge image through networks architectures

Quantitative results for the historical maps

The Validation data is year 1926 map in 1, 2 district of Paris.
The Testing data is 1898 map in 3, 4 district of Paris.

	Parameters		Validation			Test		
	δ	σ	PQ	SQ	RQ	PQ	SQ	RQ
U-Net	10.0	50.0	**60.35**	68.47	88.15	**47.12**	54.30	86.77
U-Net+VGG	1.0	50.0	57.68	65.31	88.32	36.01	41.19	87.44

Global COCO Panoptic results (in %) of our evaluation, for unet (BCE loss) and U-Net+VGG loss.

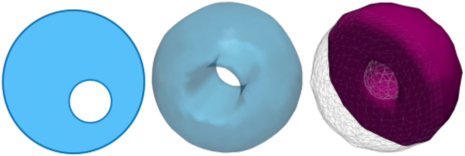
U-Net+VGG strength:

1. A new way to preserve topology of learned likelihood by using VGG features
2. Edge refinement process proves to be effectiveness in several public datasets

U-Net+VGG weakness:

1. No evidence proved that elogated VGG features have topology properties
2. There are no topology information involved in the whole process of learning

Some basis of topology



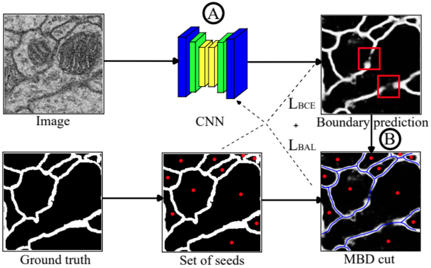
Left: a hole in 2D; Middle: A hole in 3D; Right: A cavity in 3D

Betti number β_i : Betti number in dimensional i; Describe and quantify topological differences in algebraic topology.
β_0: Number of connected components;
β_1: Number of circular holes (Closed shapes);
β_2: Number of cavities;
We are focusing the problems in first dimensional topology β_1 which is to extract closed shapes from edge images.
Why we don't simply activate object boundaries to preserve topology in EPM?

Enhancing topology of edge image through object boundaries

Boundary-awareness loss function

1. Extract object boundaries from EPM
2. Activate the object boundaries by using loss function to enhance topology properties



The pipeline of Boundary-awarness loss.

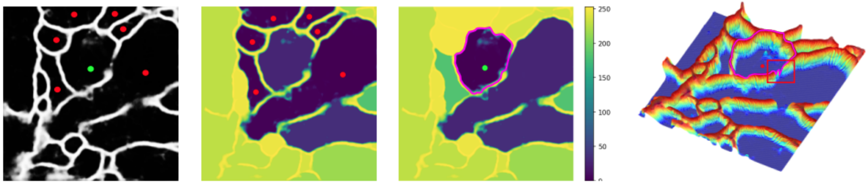
Ngoc, M. Ô. V.*, Chen, Y.*, Boutry, N., Chazalon, J., Carlinet, E., Fabrizio, J., Mallet, C Géraud, T. (2021, November). Introducing the Boundary-Aware loss for deep image segmentation. In British Machine Vision Conference (BMVC) 2021.

Enhancing topology of edge image through object boundaries

Boundary-awareness loss function

Four steps to create object boundaries:

1. Build seed relationship between neighbouring objects
2. Calculate distance maps through background objects
3. Calculate distance maps through foreground objects
4. Compare two distance maps to get object (boundaries)



(a) Likelihood image from the CNN network (b) Background MBD distance map (c) Foreground MBD distance map (d) The density map

Distance map with minimum barrier distance for foreground and background.

Enhancing topology of edge image through object boundaries

Boundary-awareness loss function

Total loss function:

$$L(x,y,w) = L_{bce}(x,y,w) + \mu L_{BALoss}(x,y) \tag{7}$$

Binary cross entropy loss:

$$L_{bce}(x,y,w) = -\sum_i (1-y_i)\cdot\log(1-f_i(x,w)) + y_i \cdot \log f_i(x,w) \tag{8}$$

Boundary-awarenss loss:

$$L_{BALoss}(x,y) = L_{mse}(x \odot C, y \odot C) \tag{9}$$

Enhancing topology of edge image through object boundaries

Quantitative results in historical map segmentation task

	Parameters		Validation			Test		
	δ	σ	PQ	SQ	RQ	PQ	SQ	RQ
U-Net	10.0	50.0	60.35	68.47	88.15	**47.12**	54.30	86.77
BALoss	1.0	50.0	**63.11**	72.02	87.63	45.65	52.90	86.30

Global COCO Panoptic results (in %) of our evaluation, for unet (BCE loss) and BALoss.

Enhancing topology of edge image through object boundaries

Strength and Weakness

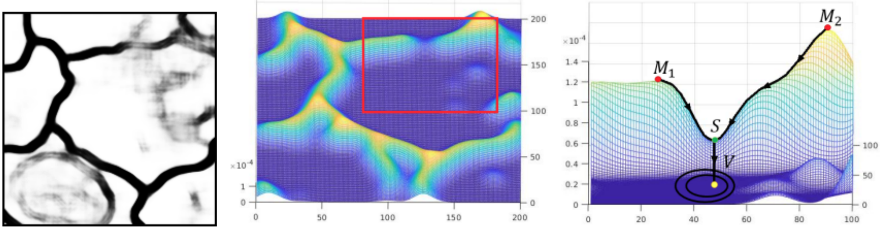
BALoss strength:

1. The BALoss activates the boundaries with strong topology properties
2. Minimum barrier distance transform can tolerate with noises in the background

BALoss weakness:

1. Activate group of pixels in the boundaries but not weak boundary (critical pixels, Leakage position)
2. Wrong boundaries if there are break pixels in boundary of objects

What is critical pixels?



An example of critical points

$$-\nabla f(x) = -[\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \frac{\partial f}{\partial x_3}, ..., \frac{\partial f}{\partial x_d}], \text{ the critical point } (\nabla f(x) = 0)$$

How to find those criticals in the EPMs?

Hu, X., Wang, Y., Fuxin, L., Samaras, D., Chen, C. (2021). Topology-aware segmentation using discrete Morse theory. arXiv preprint arXiv:2103.09992. (ICLR)

Persistent Homology!

Persistent homology: Captures all possible topological structures from all thresholds instead of fix threshold (normally we take 0.5);

Persistent diagram: Summaries topological structure into a concise format.

Birth time: Threshold value when connected components are created

Dead time: Threshold value when connected components are merged with others CC (topology properties are changed)

Mathematical definition:

Define threshold α

$1 = \alpha_1 \geq \alpha_2 \geq \alpha_3 ... \geq \alpha_n = 0$

$\emptyset = f^{\alpha_1} \subseteq f^{\alpha_2} \subseteq f^{\alpha_3} \subseteq ... f^{\alpha_n} = \Omega$ (Hierarchy of connected components)

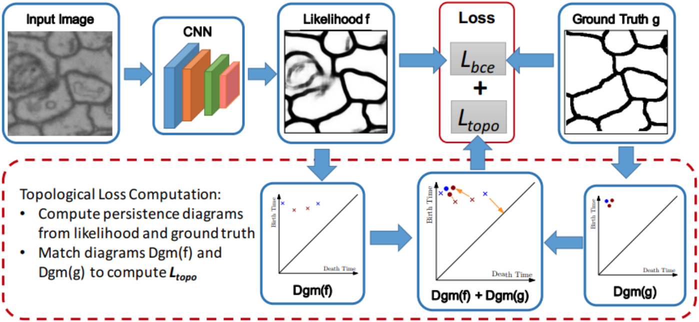
Define a persistent diagram Dgm(f) to describe f^{α_1}

Each persistent dot p = (d, b) $\in Dgm(f)$

Birth(p) = b and death(p) = d

$Dgm(f) = set(p_i), Dgm(g) = set(p_j)$ (Vector in persistent space)

1. Change predicted likelihood (epm) and ground truth into persistent diagram (persistent space)
2. Define a objective function to measure the difference between two space

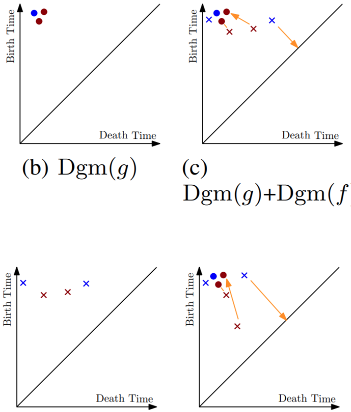


Topoloss pipline

Hu, X., Li, F., Samaras, D., Chen, C. (2019). Topology-preserving deep image segmentation. Advances in neural information processing systems, 32.

Enhancing topology of edge image through Critical points

Topoloss



(b) Dgm(g) (c) Dgm(g)+Dgm(f)

(e) Dgm(f) (f) Dgm(g)+Dgm(f')

A example of persistent dot match.

Total loss function:

$$L(x,y,w) = L_{bce}(x,y,w) + \mu L_{topo}(x,y,w) \tag{10}$$

Binary cross entropy loss:

$$L_{bce}(x,y,w) = -\sum_i (1-y_i)\cdot \log(1-f_i(x,w)) + y_i \cdot \log f_i(x,w) \tag{11}$$

Topoloss:

$$\min D(f,g) = \sum_{p\in Dgm(f)} [birth(p) - birth(\gamma^*(p))]^2 + [death(p) - death(\gamma^*(p))]^2 \tag{12}$$

Activate in critical pixels:

$$L_{topo}(f,g) = L_{mse}(f \odot Cri^*, g \odot Cri^*) \tag{13}$$

Enhancing topology of edge image through Critical points

Quantitative results

	Parameters		Validation			Test		
	δ	σ	PQ	SQ	RQ	PQ	SQ	RQ
U-Net	10.0	50.0	**60.35**	68.47	88.15	**47.12**	54.30	86.77
Topoloss	6.0	100.0	59.91	68.02	88.08	36.87	43.78	84.22

Global COCO Panoptic results (in %) of our evaluation, for unet (BCE loss) and Topoloss.

Topoloss strength:

1. First topology loss function that achieve state of the art results in deep image segmentation task.
2. The loss is proved to be differentiable and can be used with all the networks.

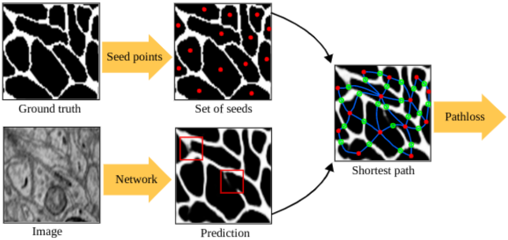
Topoloss weakness:

1. No evidence proved that the bijections of persistent dots are optimal.
2. The bijections are selected through persistent lifetime which are heuristic.
3. The results varied through different pretrain model
4. The betti number in perdiction should be as close as to the ground truth betti number for better optimization

How to correctly activate the critical points without highly limited on pretrain?

Pathloss contains four steps:

1. Get seeds from images
2. Creating shortest-path between every pairs of neighbouring seeds
3. Detecting critical pixels by intersecting ground truth with shortest-path
4. Activate the critical pixels to enhance topology properties in training

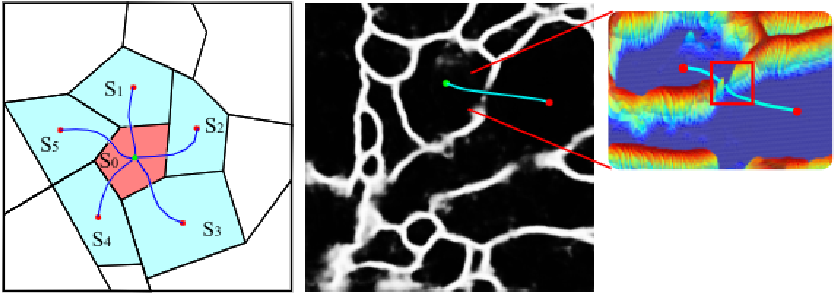


Pathloss pipline

Ngoc, M. O. V.*, Chen, Y.*, Boutry, N., Fabrizio, J., Mallet, C. (2022). BuyTheDips: PathLoss for improved topology-preserving deep learning-based image segmentation. arXiv preprint arXiv:2207.11446.(Under reivew)

Enhancing topology of edge image through Critical points

Pathloss



Pathloss example

Enhancing topology of edge image through Critical points

Pathloss

Total loss function:

$$L(x,y,w) = L_{bce}(x,y,w) + \mu L_{pathloss}(x,y,w) \tag{14}$$

Binary cross entropy loss:

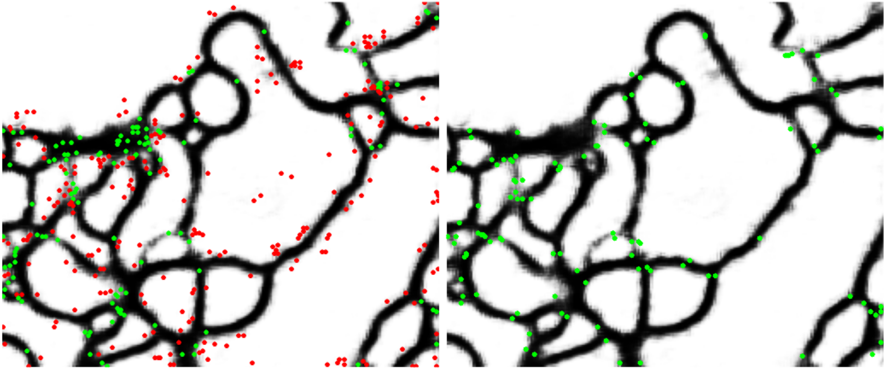
$$L_{bce}(x,y,w) = -\sum_{i}(1-y_i)\cdot\log(1-f_i(x,w)) + y_i\cdot\log f_i(x,w) \tag{15}$$

Activate in critical pixels:

$$L_{pathloss}(f,g) = L_{mse}(f\odot Cri^{*}, g\odot Cri^{*}) \tag{16}$$

Enhancing topology of edge image through Critical points

Topoloss and Pathloss critical points



Critical points of Topoloss and Pathloss;
Filtered points of Topoloss; Activate critical points

Enhancing topology of edge image through Critical points

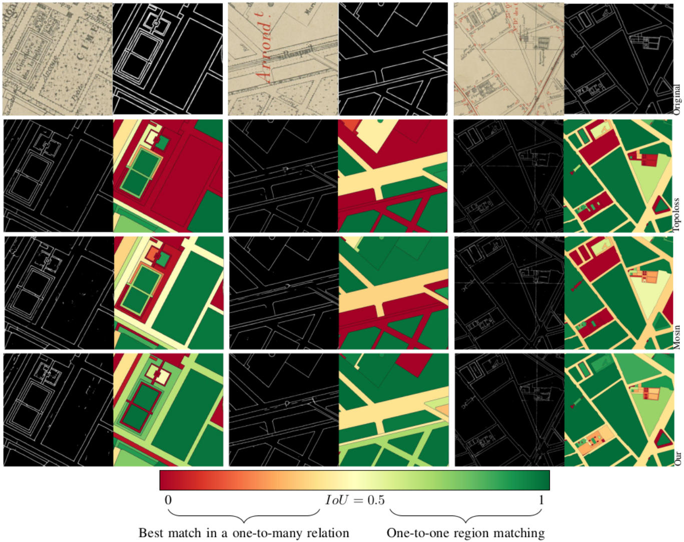
Quantitative results

	Parameters		Validation			Test		
	δ	σ	PQ	SQ	RQ	PQ	SQ	RQ
U-Net	10.0	50.0	60.35	68.47	88.15	47.12	54.30	86.77
Pathloss	3.0	100.0	**62.40**	70.57	88.42	**47.26**	54.70	86.40

Global COCO Panoptic results (in %) of our evaluation, for unet (BCE loss) and Pathloss. State-of-art in historical map segmentation task in 2021. State-of-art in ISBI12, 13 and CREMI task in 2021.

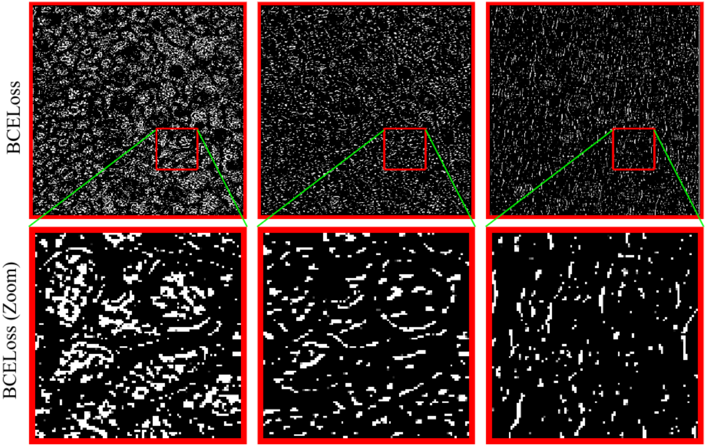
Enhancing topology of edge image through Critical points

Qualitative results of recall map



Enhancing topology of edge image through Critical points

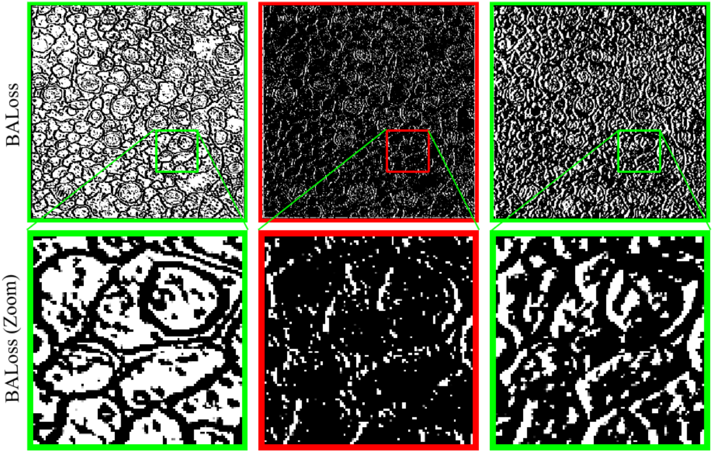
Feature analysis in @top3 weights in early stage of U-Net



Features of BCEloss.

Enhancing topology of edge image through Critical points

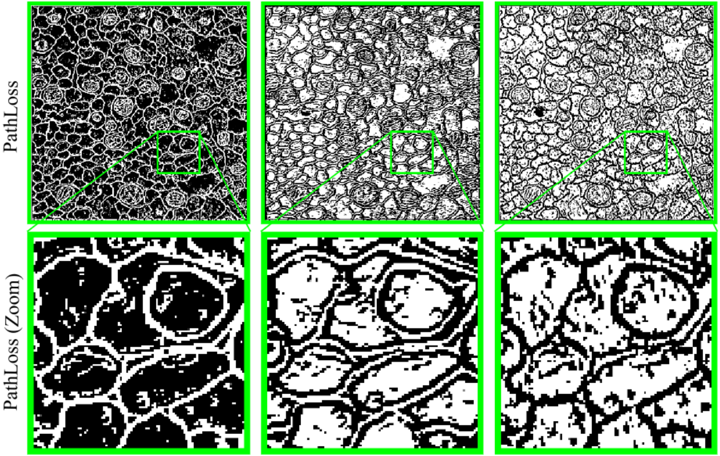
Feature analysis in @top3 weights in early stage of U-Net



Feature of BALoss.

Enhancing topology of edge image through Critical points

Feature analysis in @top3 weights in early stage of U-Net



Featues of Pathloss.

Pathloss strength:

1. Finding more accurate critical points by measuring the shortest path between seed of regions
2. Do not need good pretrain

Pathloss weakness:

1. Limited generalization power of topology properties in unseen dataset

Take home messages & Perspectives

Take home messages:

1. Improving topology properties through VGG networks proves to be inadequate.
2. Activating the correct critical points will provide better edges with topology properties.

Perspectives:

1. Leveraging the generalizability power of topology in historical map segmentation task.
2. Possibility of merging the learnable persistent homology with watershed algorithms for better seed filtering.
3. Combining meta-learning with topology preserving loss to boost the generalization power to the unseen dataset with strong topology properties.