ICTAI 2025

2025 IEEE 37th International Conference on Tools with Artificial Intelligence

3–5 November 2025
Athens, Greece

UNIVERSITY OF BUCHAREST
VIRTUTE ET SAPIENTIA

Map Generation From Overlapping Microscopy Images Using Stitching methods

hria
HUB ROMÂN
DE INTELIGENȚĂ ARTIFICIALĂ

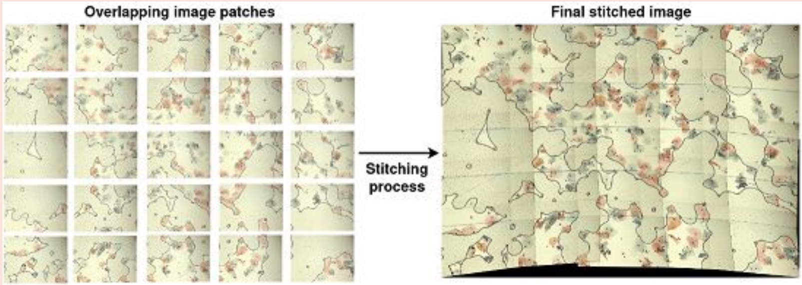
Buță Gabriel-Sebastian Ceaușescu Ciprian-Mihai Alexe Dumitru-Bogdan

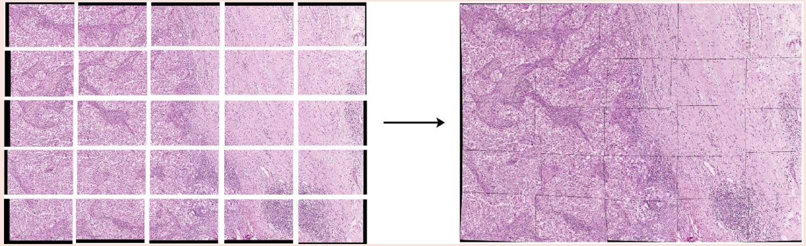
Agenda

1. Introduction
2. Datasets
3. Stitching Methods
4. Stitching Optimisations
5. Metrics
6. Results
7. Conclusions and future work

Introduction

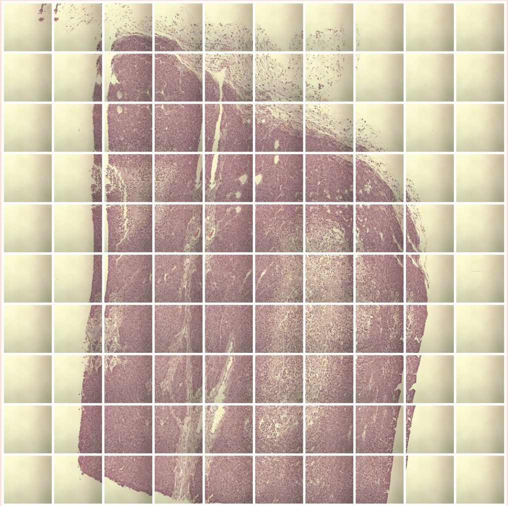
- Input-Output
  - Input: Overlapping image tiles
  - Output: High-resolution microscopy maps
- Motivation
  - Puchkov, Evgeny et al. (2016), “Image analysis in microbiology: A review,” in Journal of Computer and Communications 4.15, page 8.
- Proposed method:
  - Repeated image stitching



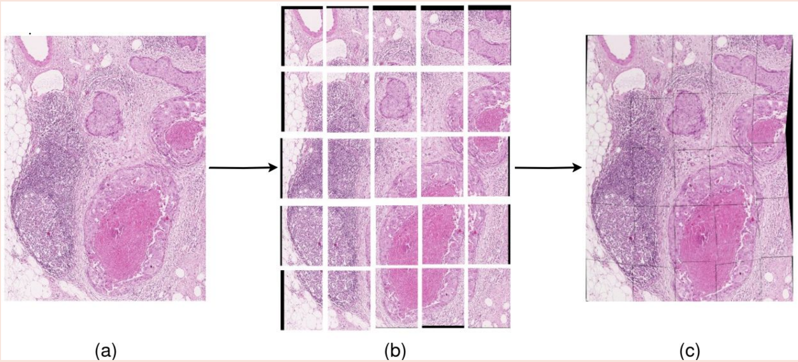


Datasets

- **Tak et al. Microscopy** Dataset
  - (Tak et al., 2020)

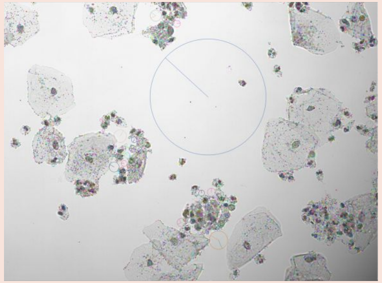


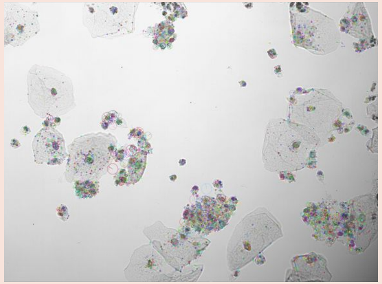
- **BCSS** Dataset
  - Breast Cancer Semantic Segmentation
  - (Amgad et. al, 2019)



Stitching Methods

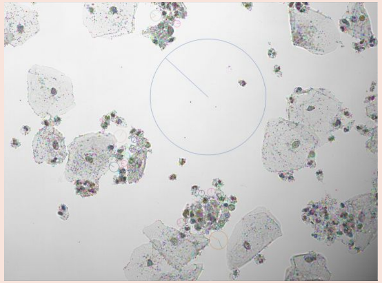
- Classic Stitching Methods
  - SIFT
  - KAZE
- Deep Learning Methods
  - SuperPoint + LightGlue
- Hybrid Methods
  - SIFT + LightGlue

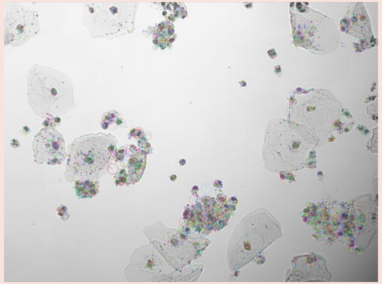




Stitching Methods

- **SIFT**: classic method to detect and describe distinctive features in images; scale and rotation-invariant.
  [Lowe, D. G. “Distinctive Image Features from Scale-Invariant Keypoints.” *International Journal of Computer Vision* 60(2), 91–110 (2004)]
- **KAZE**: classic method to detect and describe images using nonlinear scale space; sharp edge preservation.
  [Alcantarilla, P. F., Bartoli, A., Davison, A. J. “KAZE Features.” In *Computer Vision – ECCV 2012*, LNCS 7577, Springer, pp. 214–227 (2012)]
- **SuperPoint**: DL method (CNN based) that jointly detects keypoints + descriptors; robust, GPU-friendly.
  [DeTone, D., Malisiewicz, T., Rabinovich, A. “SuperPoint: Self-Supervised Interest Point Detection and Description.” In Proceedings of the IEEE/CVF CVPRW 2018]
- **LightGlue**: DL method (Transformer based) that filters/validates matches adaptively.
  [Lindenberger, P., Sarlin, P.-E., Pollefeys, M. “LightGlue: Local Feature Matching at Light Speed.” In Proceedings of the IEEE/CVF ICCV, pp. 17581–17592 (2023)]



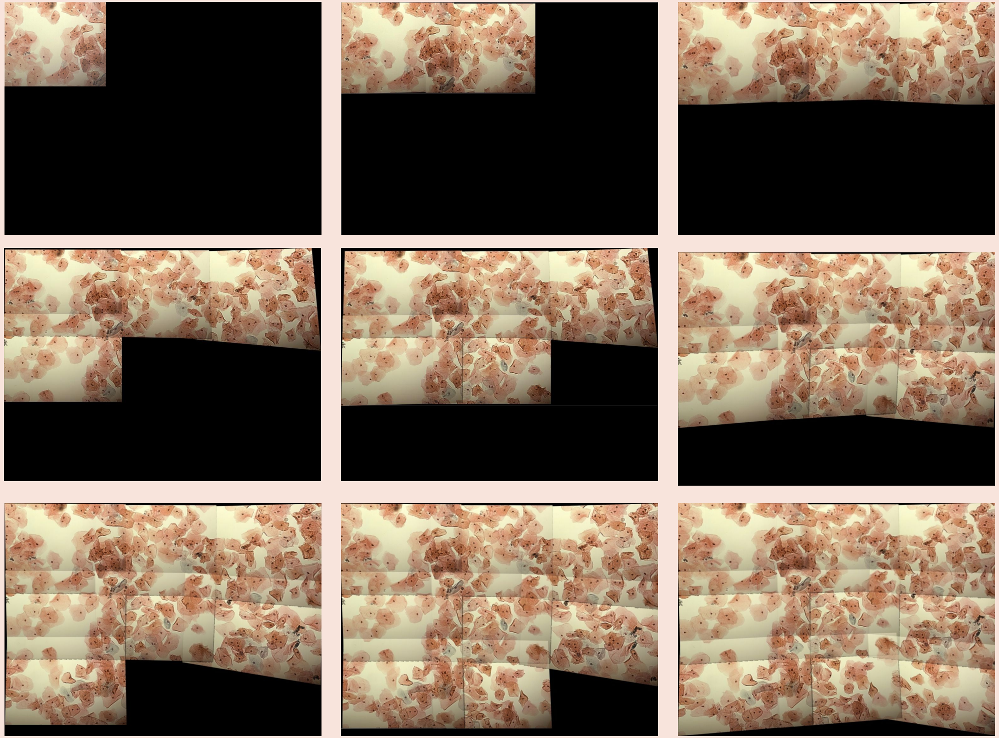


Stitching Optimisations

- Image Stitching Orders
- Pairwise stitching Optimisations

Stitching Optimisations

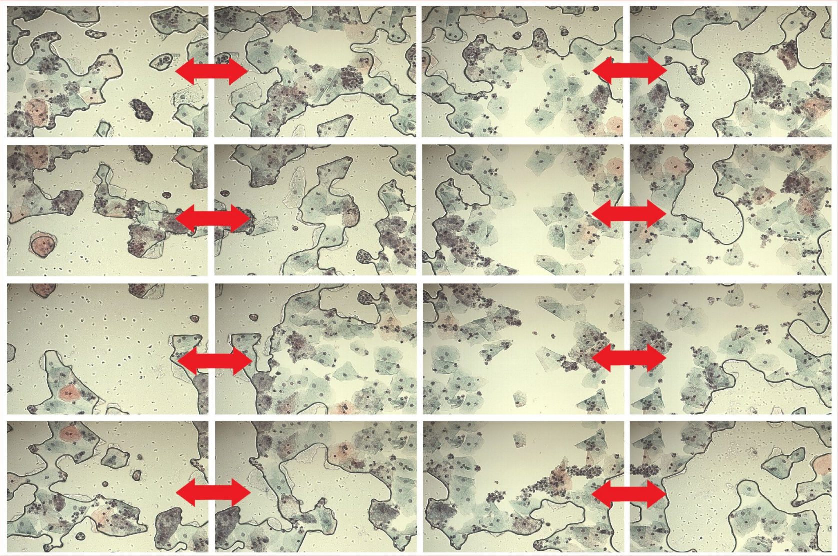
- Image Stitching Orders
  - **Matrix Order**
- Pairwise stitching Optimisations



Stitching Optimisations

- Image Stitching Orders
  - Matrix Order
  - **Divide et. Impera Order**

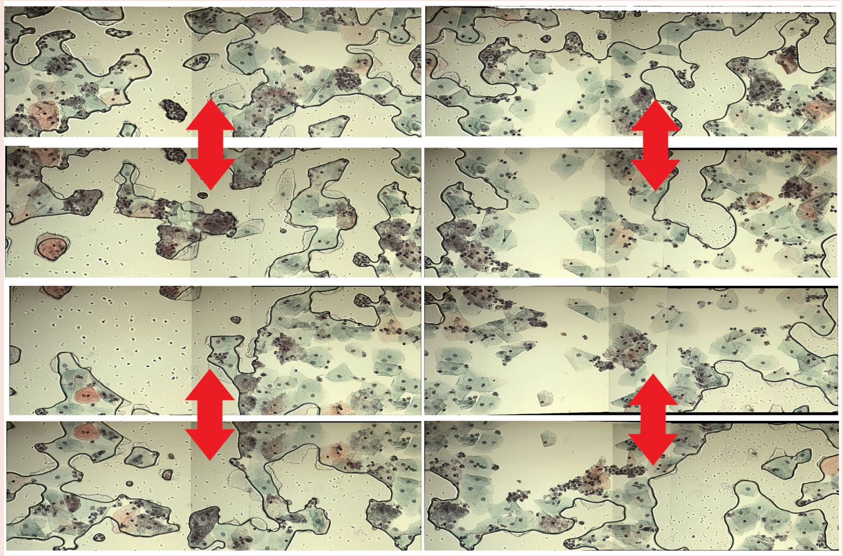
- Pairwise stitching Optimisations



Stitching Optimisations

- Image Stitching Orders
    - Matrix Order
    - **Divide et. Impera Order**

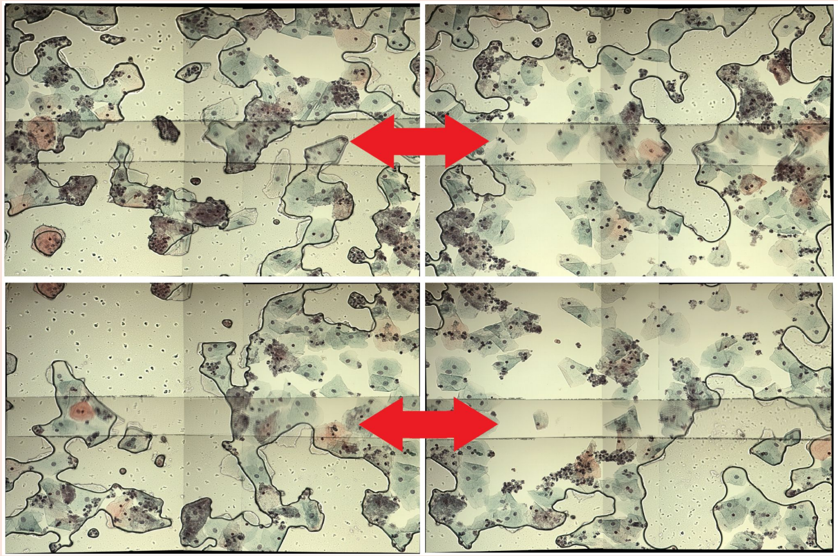
- Pairwise stitching Optimisations



Stitching Optimisations

- Image Stitching Orders
  - Matrix Order
  - **Divide et. Impera Order**

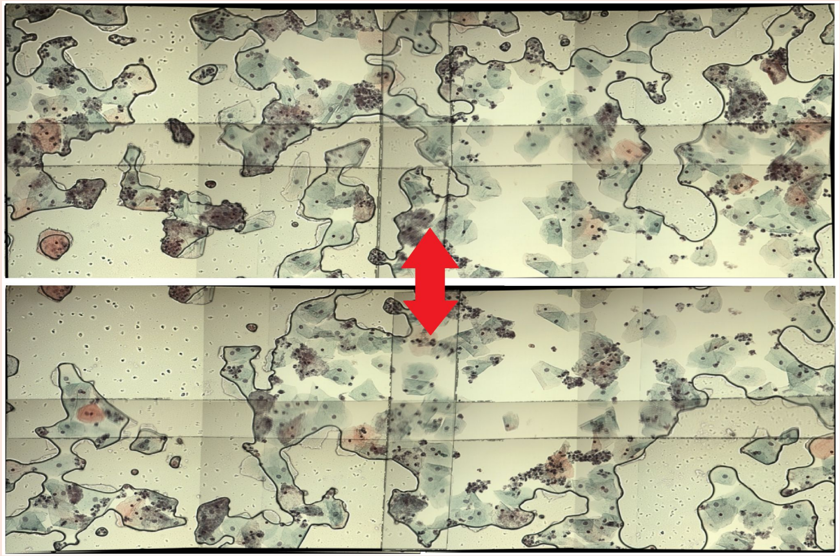
- Pairwise stitching Optimisations



Stitching Optimisations

- Image Stitching Orders
    - Matrix Order
    - **Divide et. Impera Order**

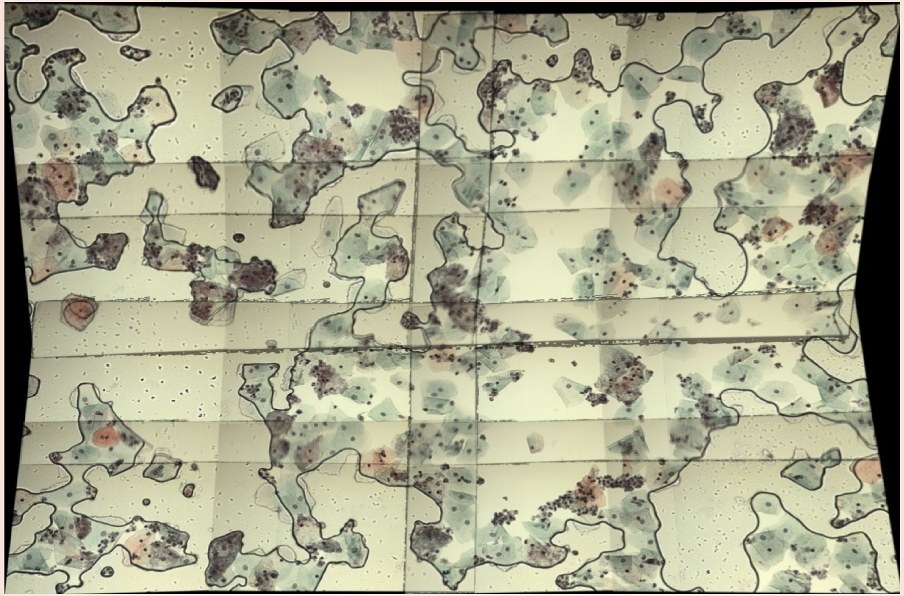
- Pairwise stitching Optimisations



Stitching Optimisations

- Image Stitching Orders
  - Matrix Order
  - **Divide et. Impera Order**

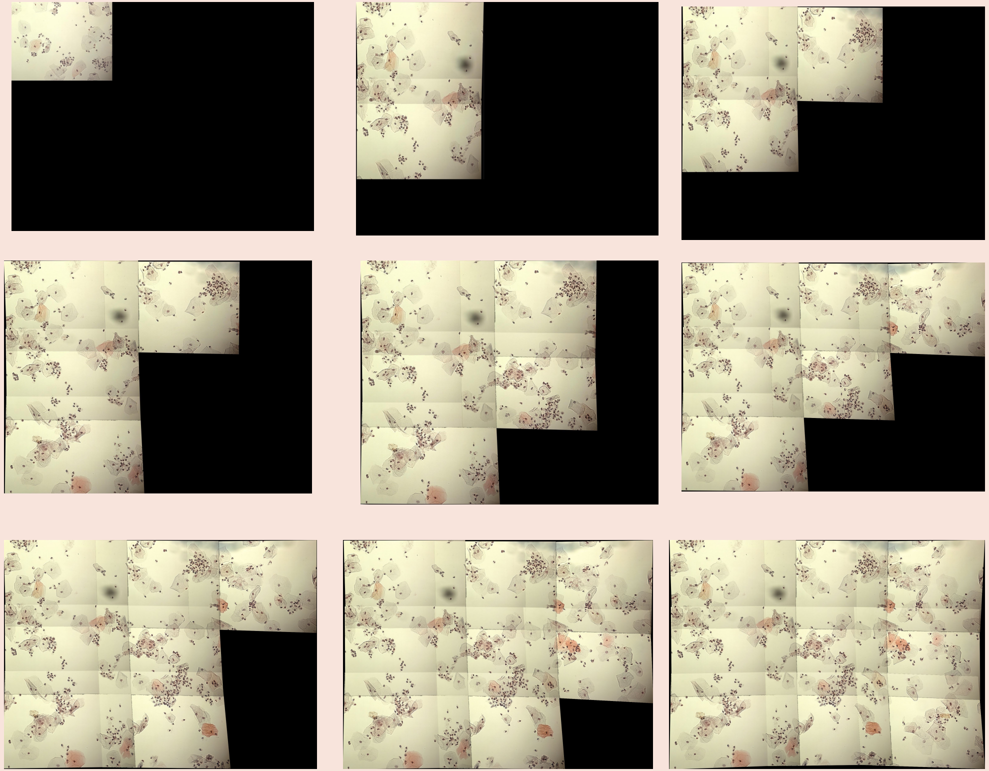
- Pairwise stitching Optimisations



Stitching Optimisations

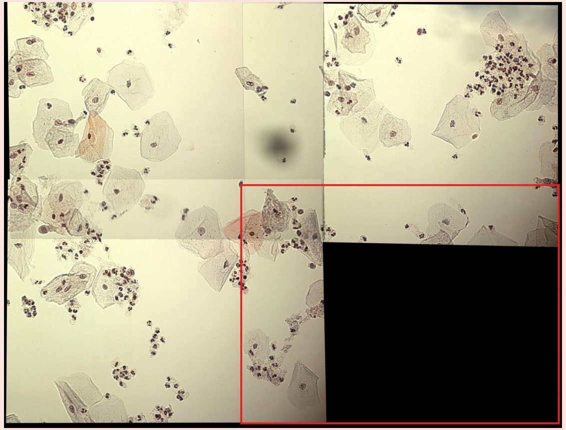
- Image Stitching Orders
  - Matrix Order
  - Divide et. Impera Order
  - **<u>Diagonal Order</u>**

- Pairwise stitching Optimisations

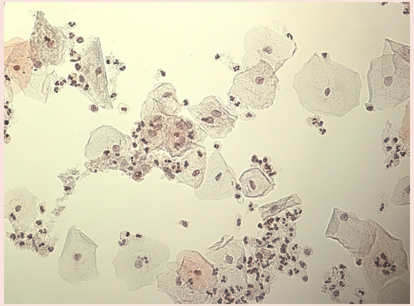


Stitching Optimisations

- Image Stitching Orders
  - Matrix Order
  - Divide et. Impera Order
  - Diagonal Order



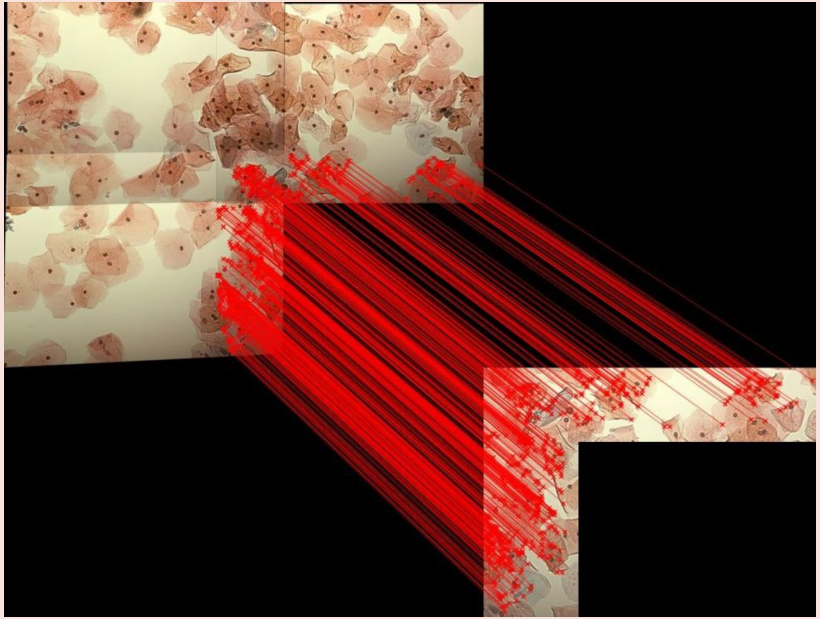
- Pairwise stitching Optimisations
  - **Matrix Sliding-Window**



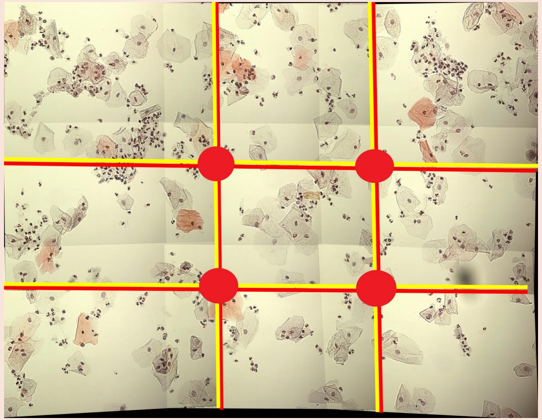
Stitching Optimisations

- Image Stitching Orders
  - Matrix Order
  - Divide et. Impera Order
  - Diagonal Order

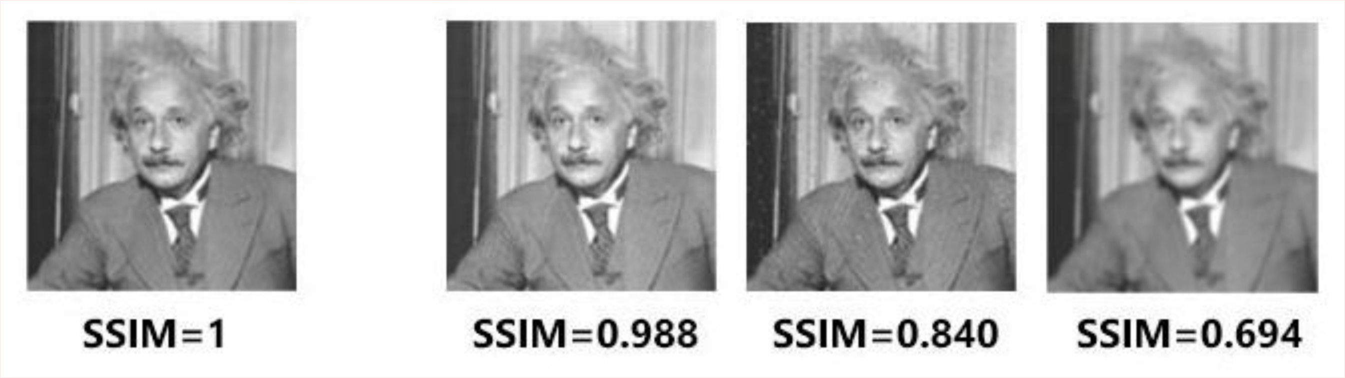
- Pairwise stitching Optimisations
  - Matrix Sliding-Window
  - **Top-Left Cutting**



Metrics **(SSIM ↑)**



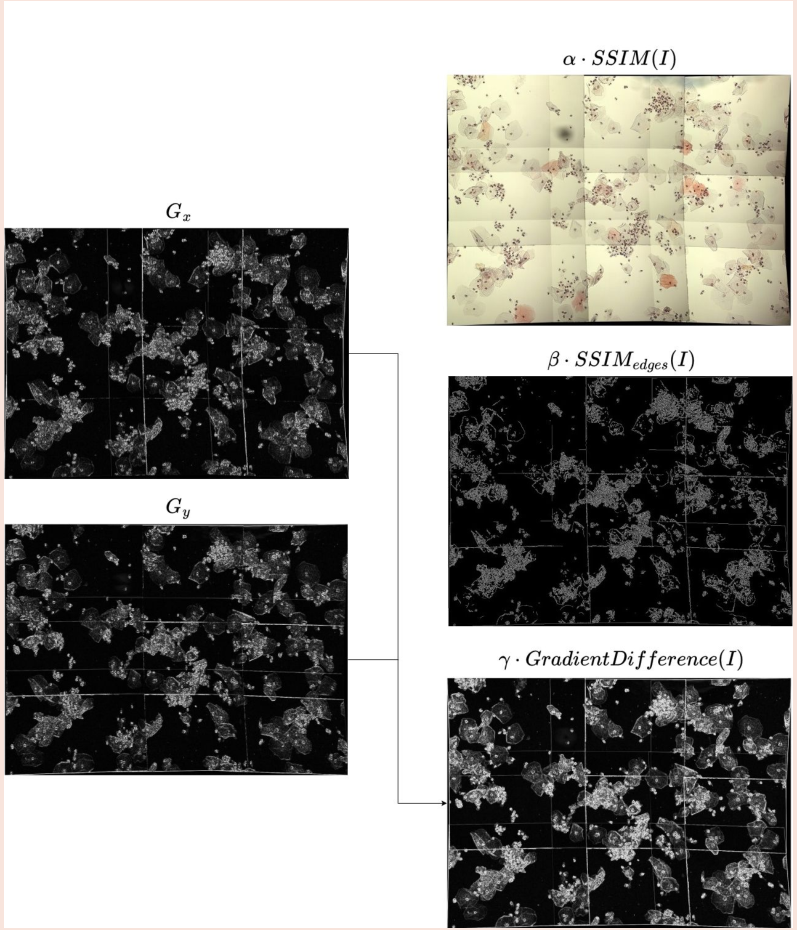
Structural Similarity Index Measure (SSIM) evaluates the perceptual similarity between two images *x* and *y* based on luminance *l*, contrast *c*, and structural alignment *s.*



Metrics **(MQ Score ↑)**

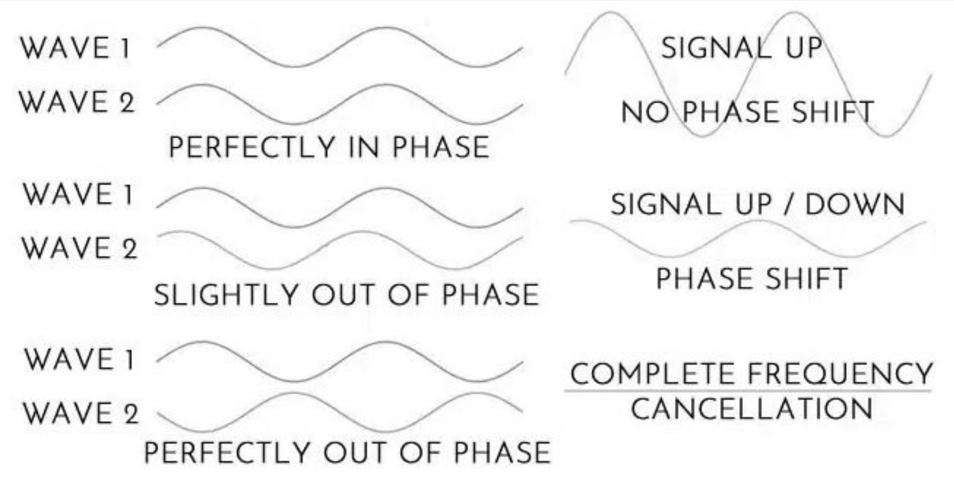
Map Quality (MQ) is a custom metric introduced in this work. It augments SSIM with edge consistency and gradient coherence.

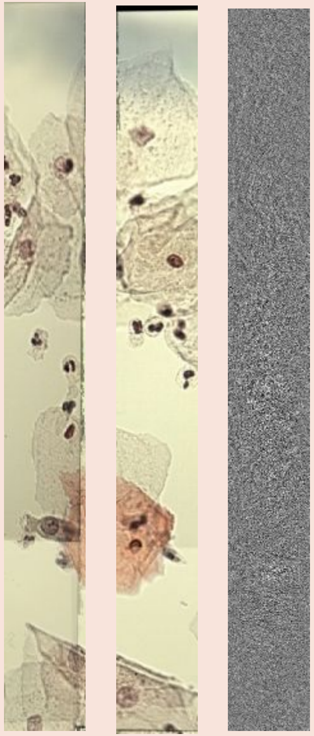
- SSIM for edges is computed on edges detected by a **Canny filter**;
- Gradient Difference is defined as the absolute difference between the gradient magnitudes (using **Sobel operator**) of the two images.



Metrics **(Phase-correlation Score ↑)**

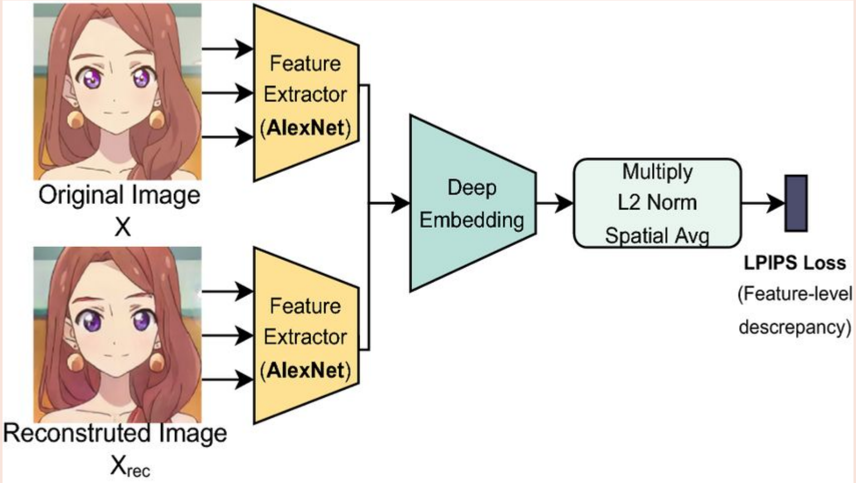
Phase-correlation is a common metric in the field of signal processing. This method strongly relies on a frequency domain representation of the data to obtain a similarity score between the proposed images.





Metrics **(LPIPS ↓)**

Learned Perceptual Image Patch Similarity (LPIPS) uses deep features from pretrained neural networks to evaluate perceptual similarity. Unlike SSIM, which operates on structural statistics, LPIPS reflects high-level visual judgments.



(Zhang et al. 2018)

Results

TABLE I: **Runtime and memory consumption of stitching methods.** Average execution time and memory usage per 5×5 tile grid.

Method	**Time (s / 5×5)**	**RAM**	**CUDA**
KAZE	≈1800	120GB	–
LG + SP	≈2580	–	≈15–20GB
LG + SIFT	≈5400	–	≈25–30GB

Results

- Diagonal order better preserves geometric consistency during expansion, likely due to its balanced stitching pattern;
- We adopt diagonal order as the default stitching strategy for all subsequent experiments.

Image name	Order	Seam SSIM (↑)	MQ (↑)	Phase-Corr. (↑)	VGG (↓)	AlexNet (↓)
194-01-70	Matrix	0.32	0.01	0.04	-	-
	Diagonal	**0.97**	**0.42**	**0.13**	-	-
	Divide	0.41	0.03	0.05	-	-
156-01-86	Matrix	0.28	0.05	0.12	-	-
	Diagonal	**0.95**	**0.42**	**0.24**	-	-
	Divide	0.32	0.01	0.09	-	-
A1A0SK	Matrix	0.18	0.01	0.08	0.96	0.98
	Diagonal	**0.89**	**0.31**	**0.50**	**0.58**	**0.75**
	Divide	0.23	0.02	0.07	0.95	0.98
ANA0SK	Matrix	0.26	0.06	0.07	0.97	0.99
	Diagonal	**0.86**	**0.25**	**0.46**	**0.61**	**0.76**
	Divide	0.34	0.04	0.11	0.96	0.98

TABLE II: **Image ordering results.** Samples where all stitching orders produced valid maps, enabling direct comparison.

Results

TABLE III: **Performance of the stitching process using different feature-matching methods on the Tak dataset.**

Metric	Model	Image Name (Tak dataset)										Average
		194-01-70	156-01-86	234-01-67	53-03	051-04-80	49-01	33-03	31-01	026-01-91	36-01	
Seam SSIM Score (H↑)	KAZE	0.9738	**0.9819**	0.9795	0.9052	0.9350	0.9453	0.9644	**0.9795**	–	0.9420	N/A
	LG + SP	0.9880	0.9525	0.9750	0.9127	0.9545	0.9617	0.9802	0.9680	0.9340	0.9550	0.9581
	LG + SIFT	**0.9884**	0.9675	**0.9801**	**0.9163**	**0.9834**	**0.9795**	**0.9931**	0.9770	**0.9547**	**0.9677**	**0.9707**
MQ Score (H↑)	KAZE	0.4244	0.4208	0.3850	0.3311	0.2927	0.4268	0.4329	0.4367	–	**0.4508**	N/A
	LG + SP	0.4247	0.4455	0.3690	0.3966	0.4070	**0.4930**	0.4403	**0.5215**	0.4420	0.3960	0.4425
	LG + SIFT	**0.4253**	**0.4669**	**0.4096**	**0.3989**	**0.4401**	0.4560	**0.4819**	0.5002	**0.4811**	0.4320	**0.4492**
Phase Corr. Score (Mean) (H↑)	KAZE	0.1342	**0.3160**	0.1765	**0.1295**	0.0728	0.0195	0.1041	0.1651	–	0.1023	N/A
	LG + SP	**0.2515**	0.2404	0.1791	0.1214	0.2202	0.2101	0.2015	**0.4762**	0.2301	0.1121	0.2242
	LG + SIFT	0.2282	0.2508	**0.1849**	0.1268	**0.3014**	**0.2165**	**0.2484**	0.4021	**0.2382**	**0.1429**	**0.2340**

Results

TABLE IV: **Performance of the stitching process using different feature-matching methods on the BCSS dataset.**

Metric	Model	Image Name (BCSS dataset)										Average
		A1A0SK	ANA0XU	AOA03U	BHA0WA	C8A12V	C8A26X	D8A1JG	D8A1JL	D8A142	D8A143	
Seam SSIM Score (H↑)	KAZE	–	–	–	0.8838	–	**0.9342**	–	**0.9789**	0.9506	0.8570	N/A
	LG + SP	0.8938	**0.8713**	0.8982	0.8572	0.8460	0.8799	0.8824	0.9200	**0.9515**	0.8551	0.8855
	LG + SIFT	**0.9865**	0.8633	**0.9252**	**0.8887**	**0.8318**	0.8405	**0.9056**	0.9224	0.9178	**0.8586**	**0.8937**
MQ Score (H↑)	KAZE	–	–	–	**0.2834**	–	0.3673	–	**0.4125**	0.3419	**0.5076**	N/A
	LG + SP	0.3171	0.2556	0.3135	0.2331	**0.2314**	**0.4072**	0.2466	0.3053	**0.3595**	0.2574	0.2943
	LG + SIFT	**0.4400**	**0.2645**	**0.3623**	0.2709	0.2138	0.2365	**0.3087**	0.3115	0.3384	0.2552	**0.3001**
Phase Corr. Score (Mean) (H↑)	KAZE	–	–	–	0.5953	–	**0.6403**	–	**0.4368**	0.6292	0.4112	N/A
	LG + SP	0.5040	0.4692	**0.6802**	0.7561	0.7832	0.5036	0.8315	0.4216	0.2861	0.2198	0.5455
	LG + SIFT	**0.5380**	**0.4754**	0.6764	**0.8165**	**0.8249**	0.5083	**0.8562**	0.4302	**0.8261**	**0.6678**	**0.6219**
LPIPS-VGG (L↓)	KAZE	–	–	–	0.5839	–	0.5902	–	0.6404	**0.5728**	0.6099	N/A
	LG + SP	**0.5869**	0.6245	0.6347	**0.5651**	0.6221	0.6023	**0.6004**	**0.5924**	0.6115	0.6353	0.6075
	LG + SIFT	0.6143	**0.6147**	**0.6142**	0.5684	**0.6055**	**0.5872**	0.6075	0.6057	0.5619	**0.6030**	**0.5982**
LPIPS-AlexNet (L↓)	KAZE	–	–	–	0.7598	–	0.7505	–	0.8466	0.7316	0.7675	N/A
	LG + SP	**0.7551**	0.7727	**0.6143**	**0.7285**	**0.7871**	0.7801	**0.7590**	**0.7873**	0.7986	0.8516	0.7634
	LG + SIFT	0.7864	**0.7625**	0.6348	0.7280	0.7910	**0.7481**	0.7720	0.8009	**0.7179**	**0.7877**	**0.7529**

Results

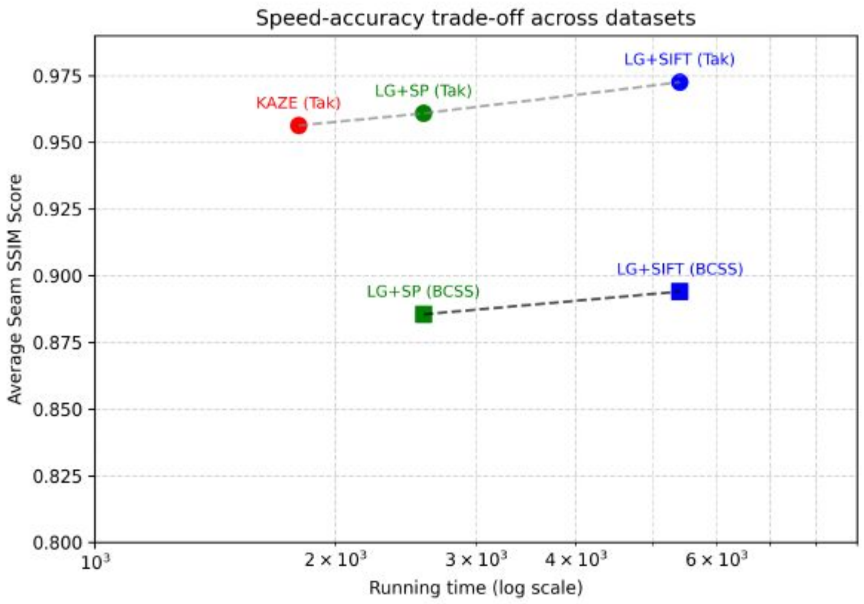


Fig. 8: **Speed-accuracy trade-off across datasets**. Comparison of runtime (log scale) versus Average Seam SSIM Score for different feature-matching pipelines on the Tak (circles, gray dashed line) and BCSS (squares, black dashed line) datasets. Hybrid methods (LG+SIFT) achieve the highest accuracy but incur significant runtime, fully deep learning methods (LG+SP) strike a favorable balance, and classical methods (KAZE) are faster but less reliable.

Conclusions ...

- Scalable whole-slide reconstruction for pathology and biomedical research, unlocking richer downstream analyses.

- Optimized deep-learning pipelines—especially those using LightGlue—consistently outperform classical stitching in alignment quality and robustness while remaining computationally practical.

… and future work

- Explore **MatchAnything** (https://zju3dv.github.io/MatchAnything/) as keypoint detection & matching;
- Estimate the displacement between two images by searching within the narrow ranges and computing the Pearson correlation (over RGB) between overlapping patches;
- Extend to other datasets;
- Apply the algorithm on a microscope scanner.

Thank you!

Ευχαριστώ!

Q&A