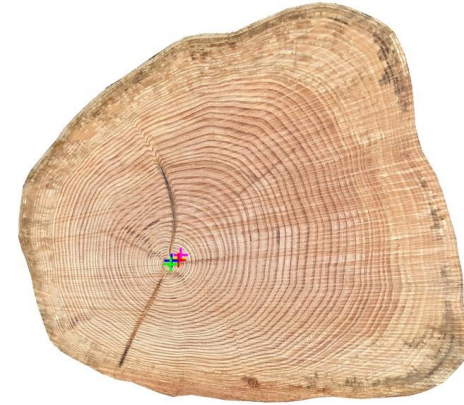


Automatic Wood Pith Detector: Local Orientation Estimation and Robust Accumulation

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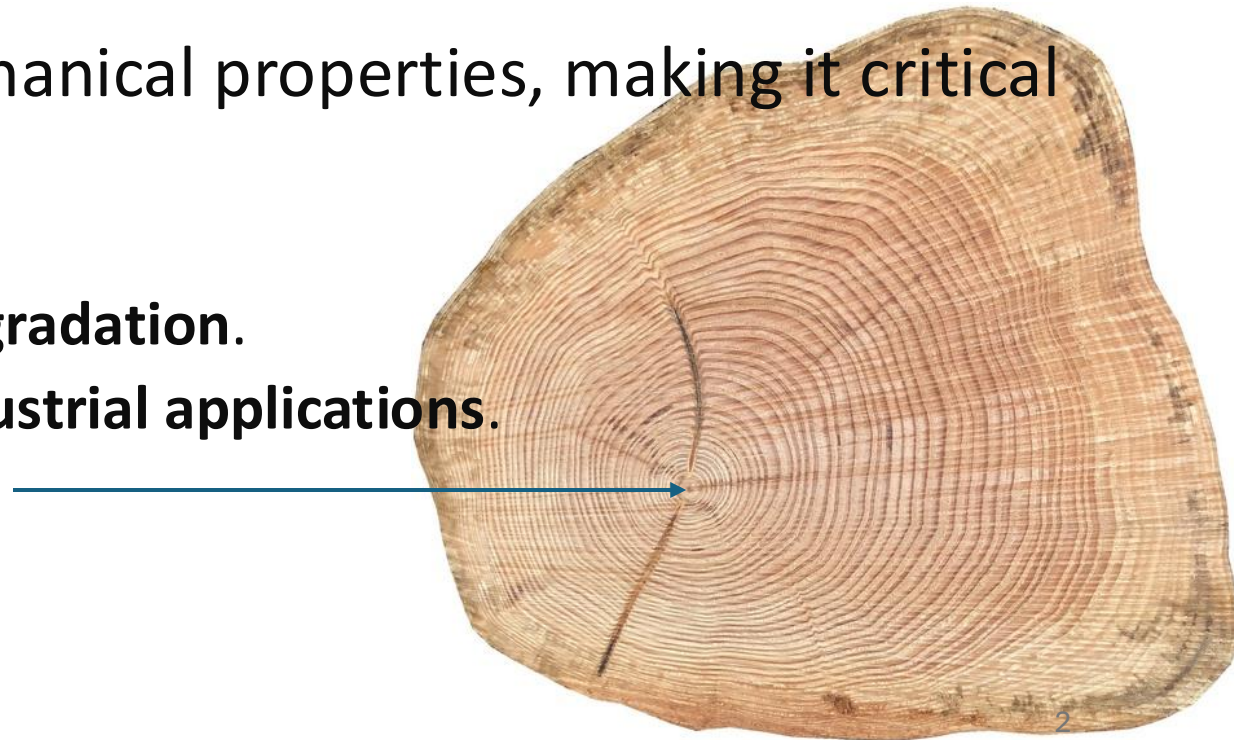
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Why is Pith Detection Important?

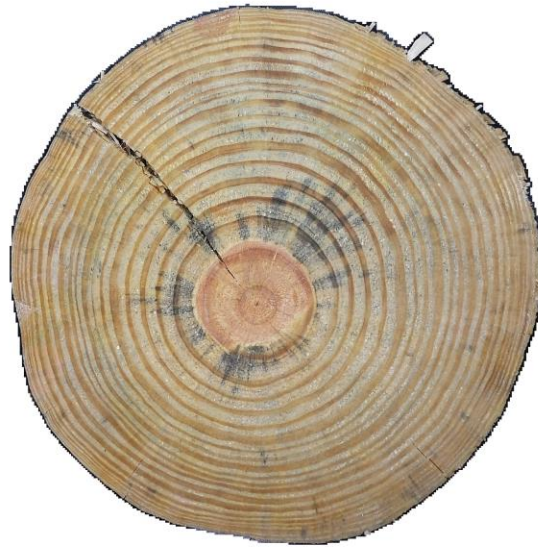
- Essential for determining the **first year of growth** and estimating **tree age**.
- The pith has distinct physical-mechanical properties, making it critical for:
 - Detecting **growth eccentricity**.
 - Identifying areas prone to **fungal degradation**.
 - Distinguishing wood sections for **industrial applications**.

Pith



Challenges in Pith Detection

- Natural wood irregularities
 - **Ring asymmetries, cracks, knots, and fungal degradation.**



Challenges by Species

- **Species diversity**
 - Gymnosperms and angiosperms exhibit different wood structures.



Pinus Taeda



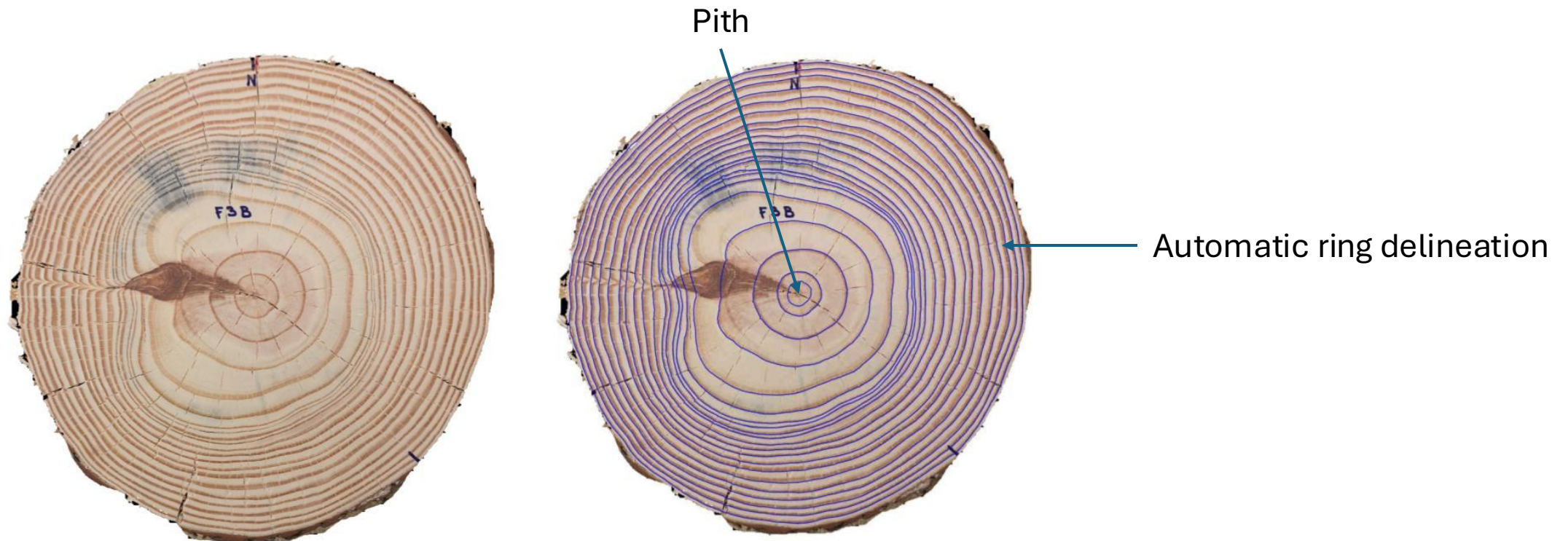
Douglas Fir



Gleditsia triacanthos

Automatic Ring Detection

- Automatic Tree Ring delineation algorithms sensitive to precise pith location, especially those relying on the **concentric ring pattern**

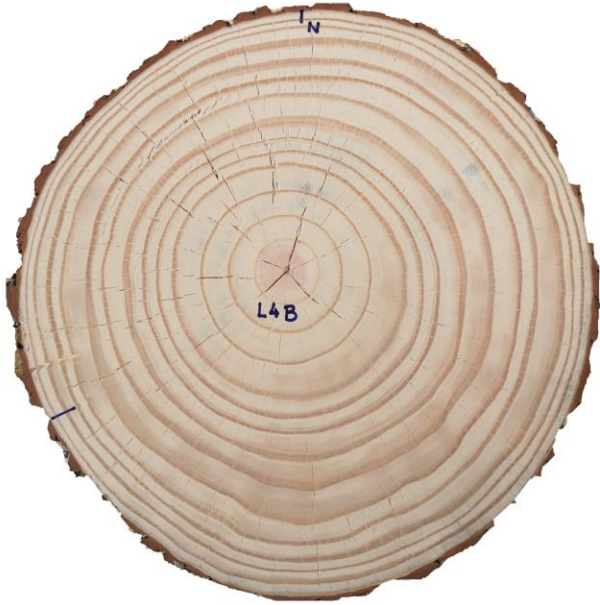


Objective

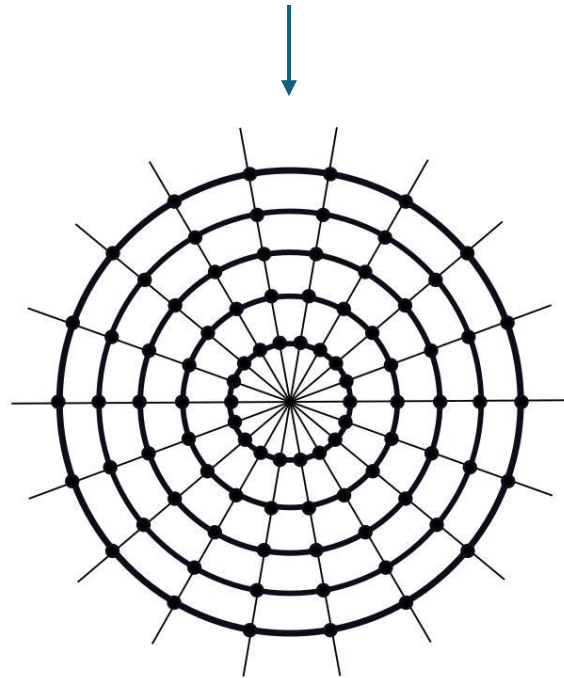
- Develop automated, reliable method for pith detection that handle variability across species, conditions, and structural irregularities.



Tree Disk Structure



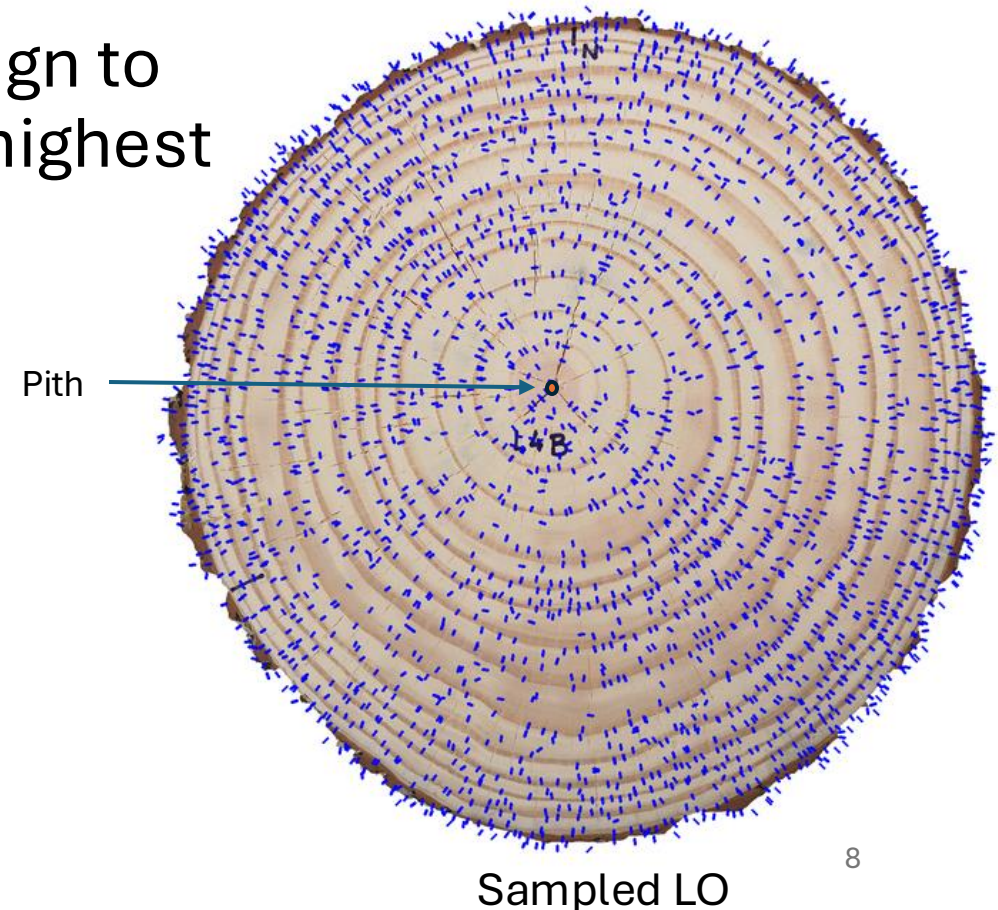
Tree disk model



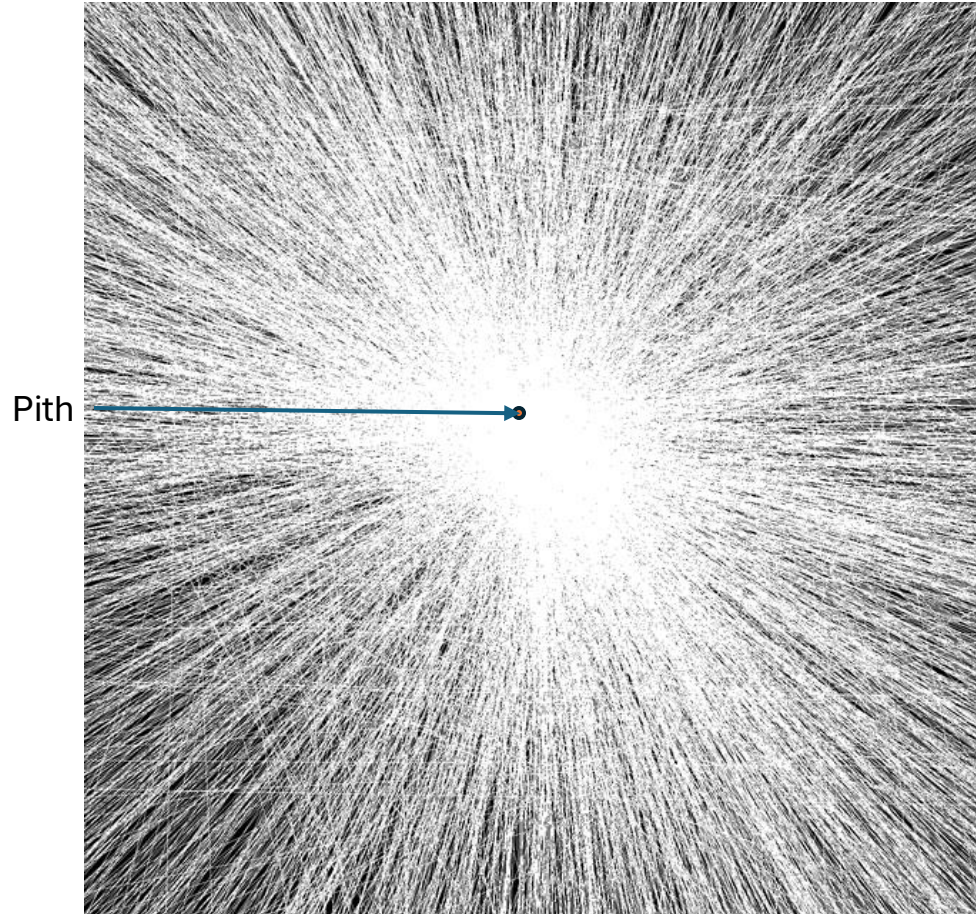
- Two main structures
 - Tree Rings formed by roughly concentric curves
 - Radial structures such as cracks and fungi
- Intersection of the lines supported by radial structures and the perpendicular to the rings is close to the pith

Computing Ring Normals

- Local orientation (LO) estimation at each pixel
 - 2D-Structure Tensor
- Splitting the image in patches, we assign to each patch the local orientation with highest coherence
- Some LOs are going to be noise



Accumulation Space



- Accumulating the LOs we can see how the pith region is highlighted.
- In order to have an accurate pith localization we need a way of accumulate them intelligently.
 - Removing LO that does not belong to the ring structure

Alignment-Based Detection

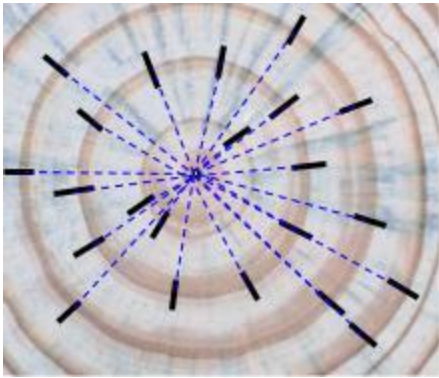


Fig1

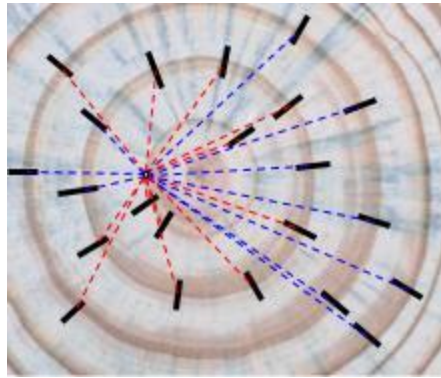


Fig2

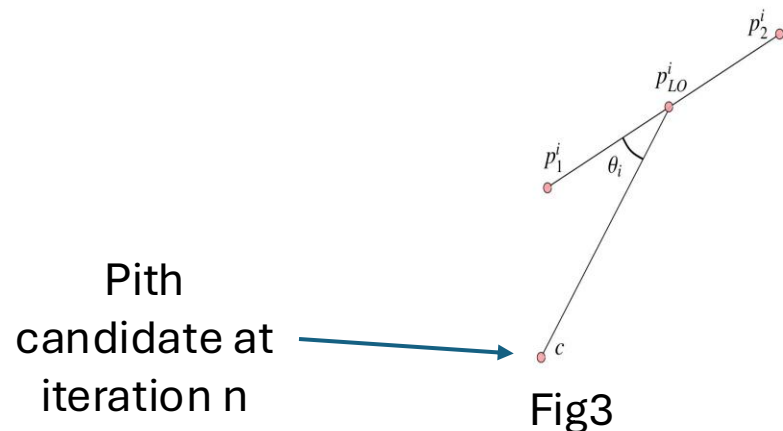


Fig3

- Intuitively the angle (Θ_i) between the pith position and the pixel belonging to the ring (p_{LO}^i) and **LO** $p_1^i p_2^i$ should be close to 0 (or 180).
 - If Θ_i is close to 0, $\cos^2(\Theta_i)$ is close to 1.

$$h(x, y) = \frac{1}{N} \sum_{i=1}^N \cos^2(\Theta_i(x, y))$$

$$\cos(\theta_i(x, y)) = \frac{\overline{cp_{LO}^i} \cdot \overline{p_1^i p_2^i}}{|cp_{LO}^i| |p_1^i p_2^i|}$$

Refinement Process

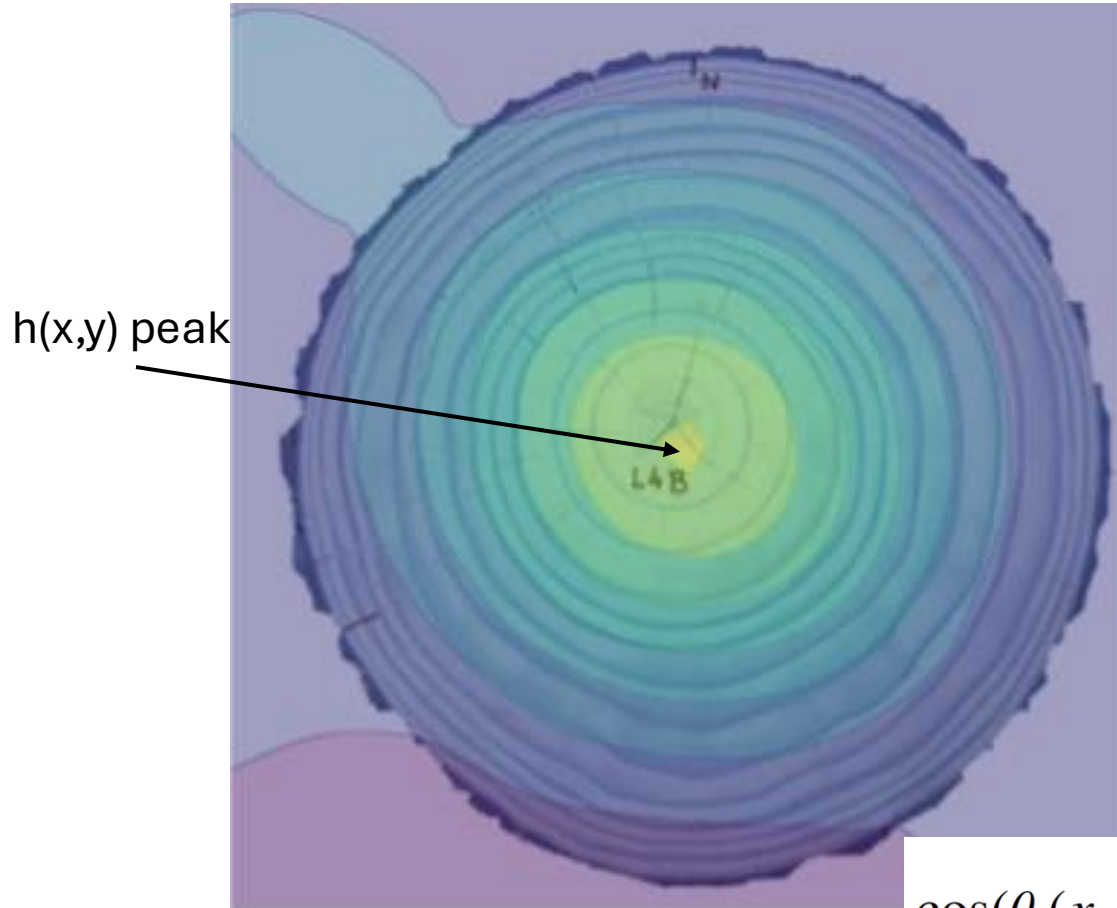


Fig1 h(x,y) level curves

$$h(x, y) = \frac{1}{N} \sum_{i=1}^N \cos^2(\Theta_i(x, y))$$

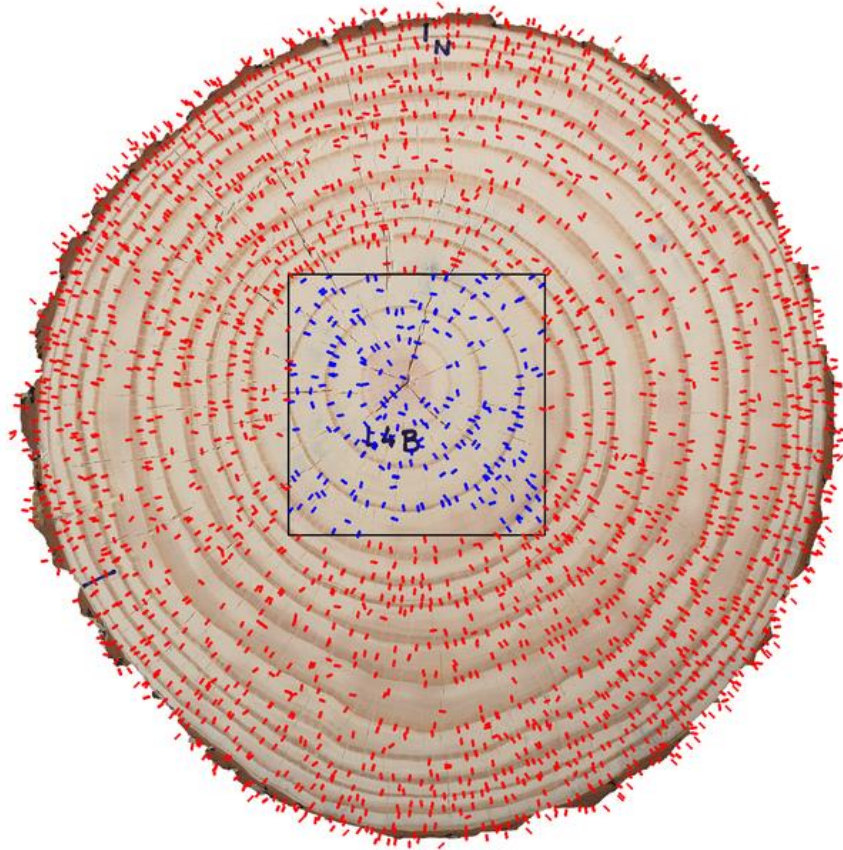
- Pith candidate

$$c_{opt} = \max_c \frac{1}{N} \sum_{i=1}^N \left(\frac{\langle \overline{cp_{LO}^i}, \overline{p_1^i p_2^i} \rangle}{|\overline{cp_{LO}^i}| |\overline{p_1^i p_2^i}|} \right)^2$$

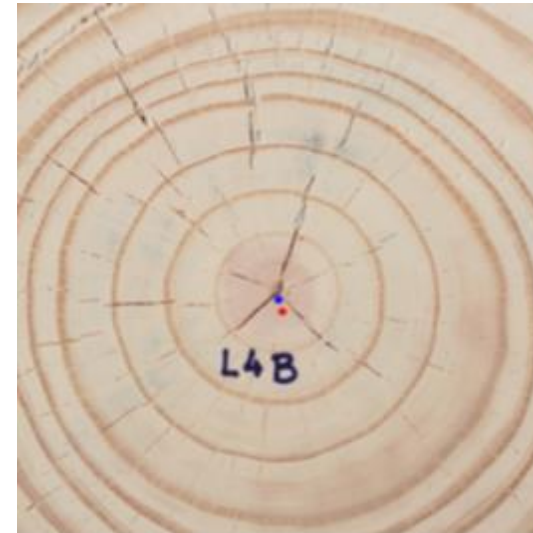
s.t. $c \in \text{Slice Region}$

$$\cos(\theta_i(x, y)) = \frac{\langle \overline{cp_{LO}^i}, \overline{p_1^i p_2^i} \rangle}{|\overline{cp_{LO}^i}| |\overline{p_1^i p_2^i}|}$$

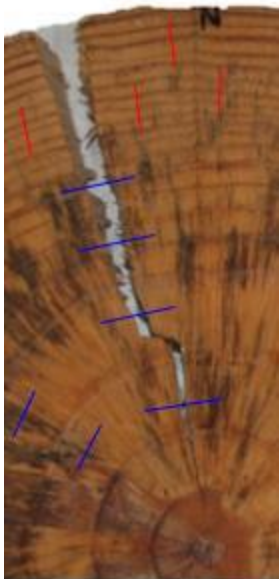
Iterative Refinement



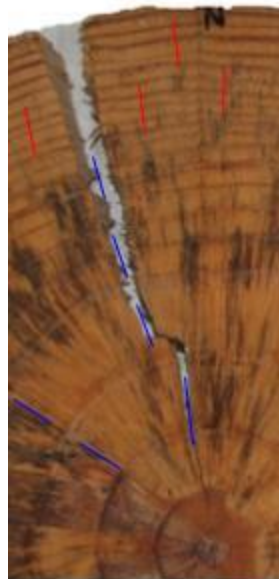
In blue colors is the sub image built around the solution c_1 obtained after the first iteration



Challenges with Anomalies



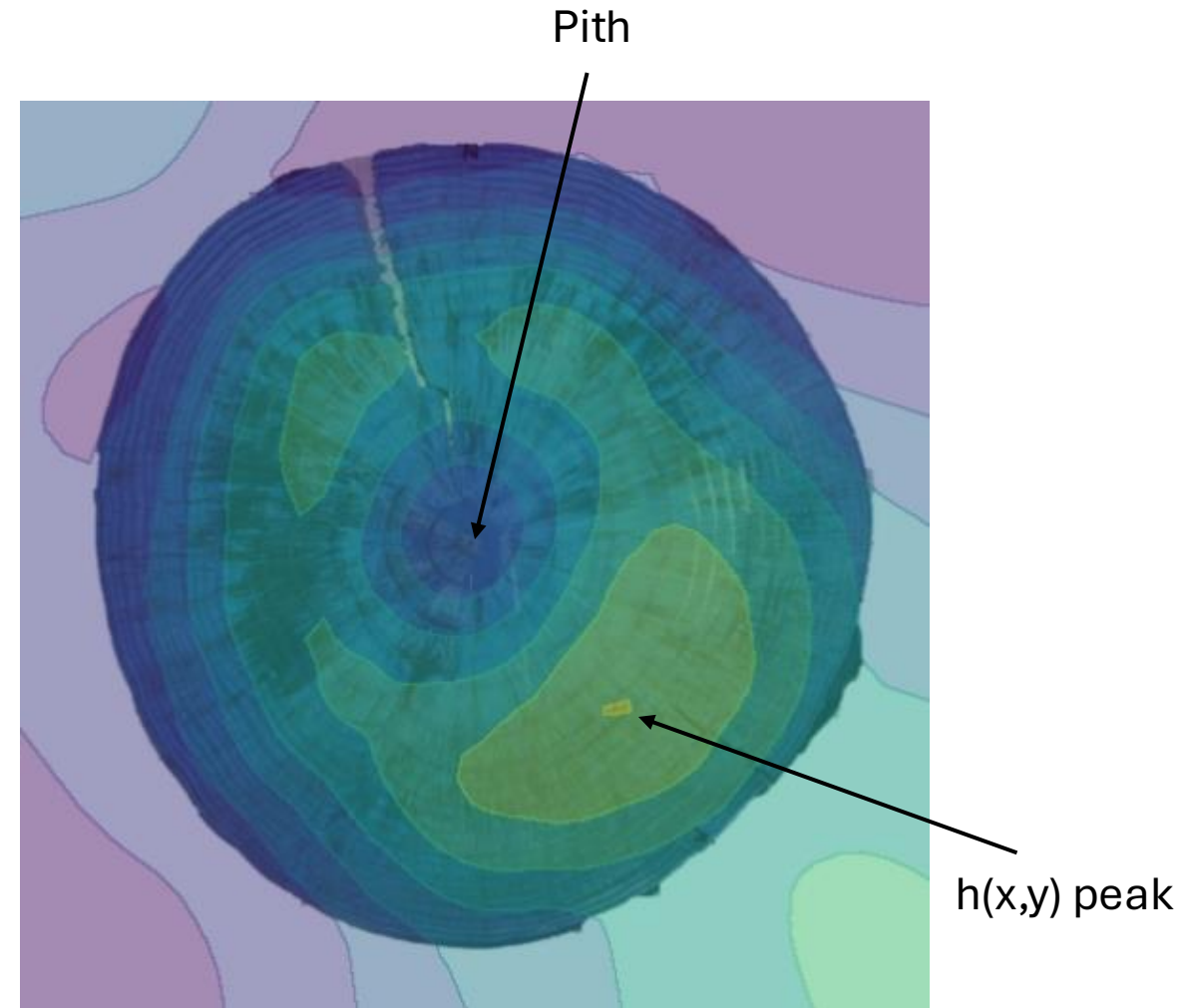
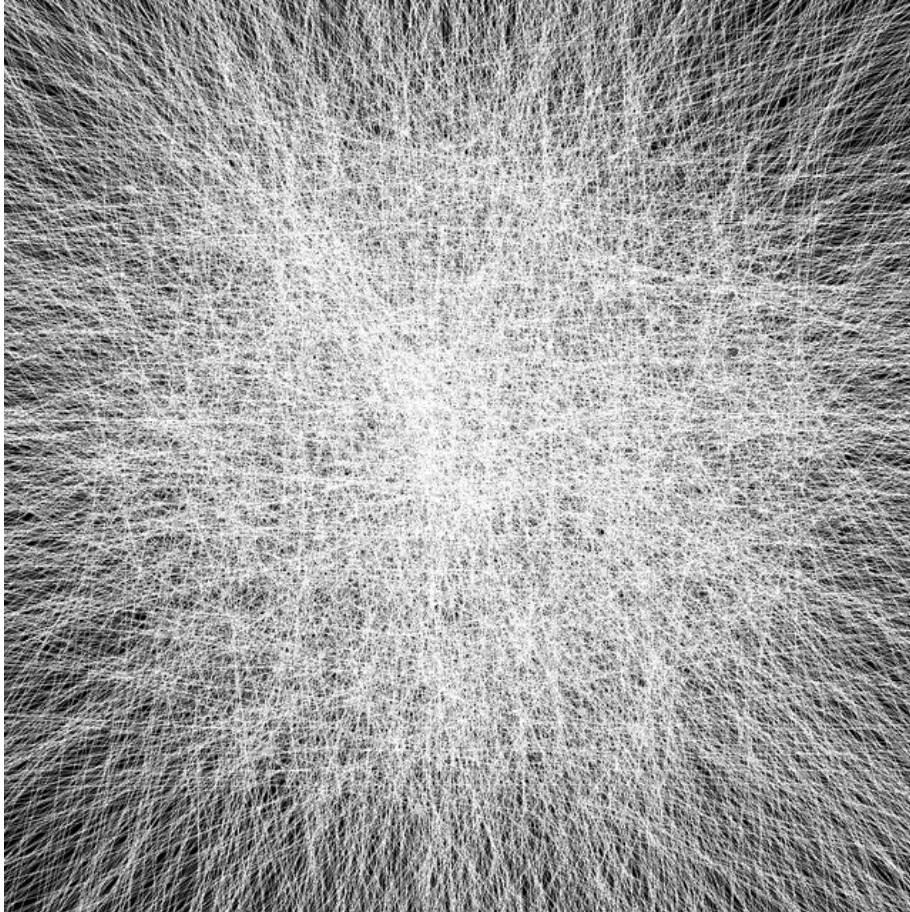
Original LOs



Blue LOs rotated 90
degrees

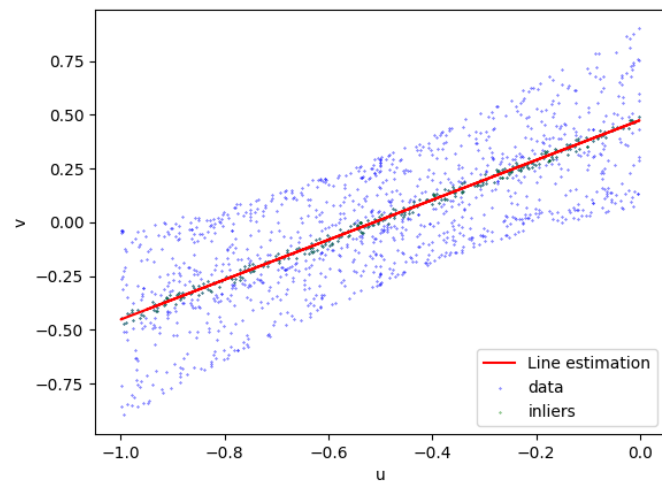
- There are situations where the ring structures not give enough information due to fungi or other perturbations.
- If we can select the LO supported by the radial structures of those perturbations and the normal of the ring structures we could rotate 90 degrees the tangential LOs (blue)

Accumulation Space with Anomalies

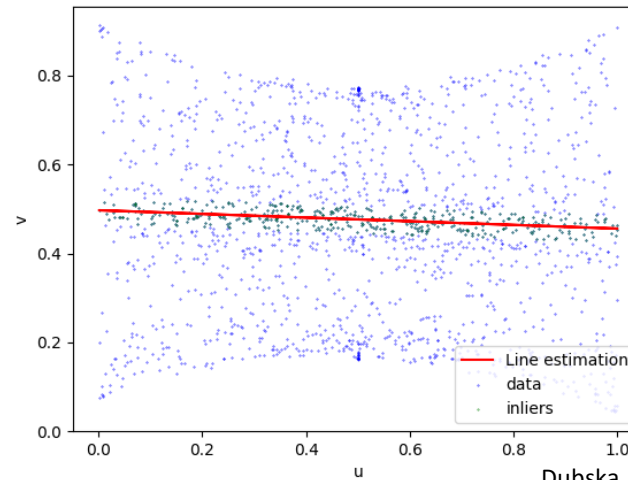


Parallel Coordinate Space

- Parallel Coordinate Space,
 - Lines are transformed as dots
 - Converging lines are aligned dots
 - It is composed by two sub-spaces: Twisted and Straight, lines with orientations between 180 and 360 degrees goes to the Twisted, lines with orientation between 0 and 180 degrees goes to the Straight



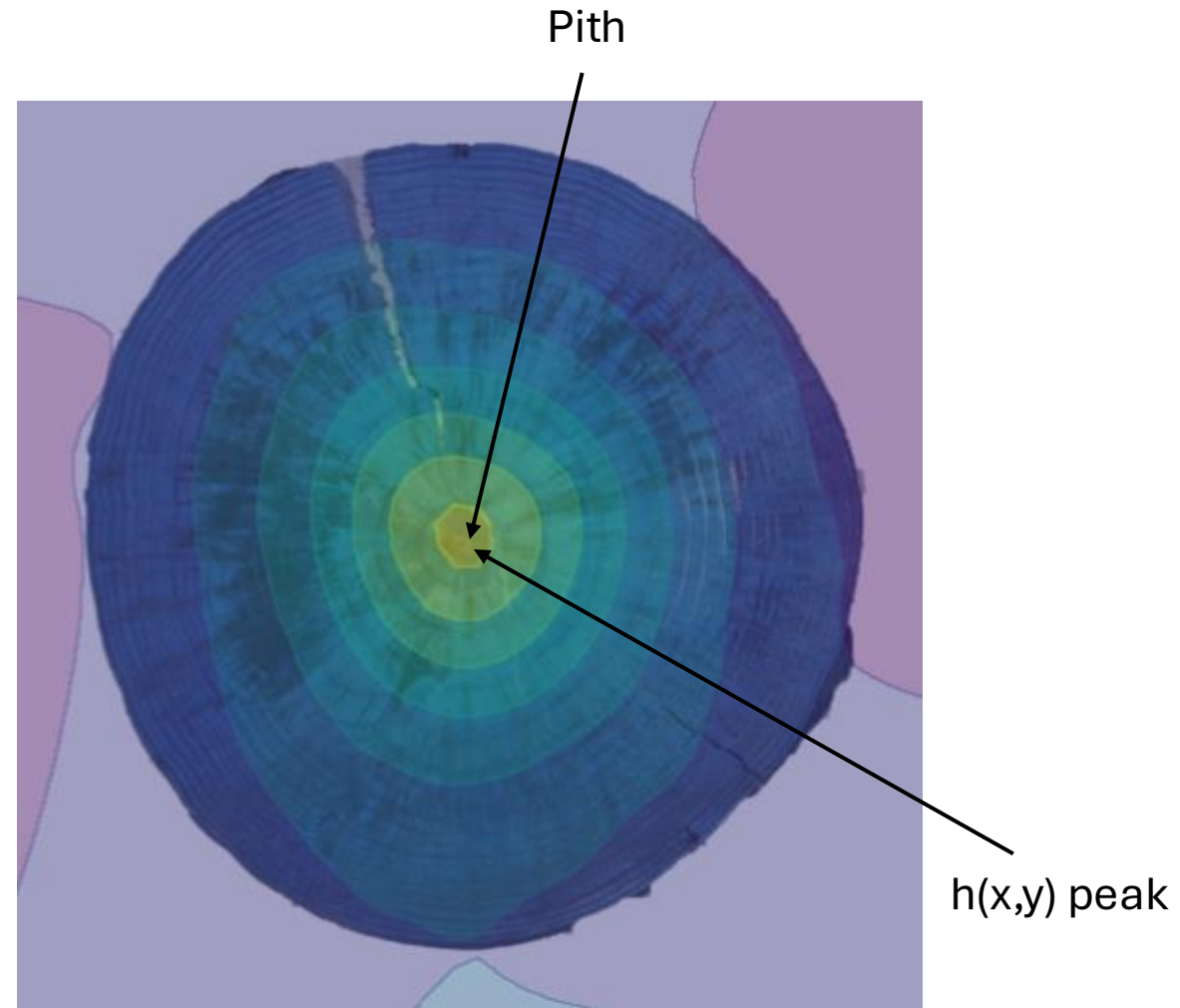
Twisted



Straight

Aligned lines are selected
using Ransac Method

Refined Accumulation Space



Deep Learning Approach: APD-DL

- **YoloV8 Network**

- Architecture designed for object detection and segmentation.
- Inspired by Kurdthongmee et al. (2019, YoloV3).
- Dataset: Wood cross-section images labeled with pith location as bounding boxes (1/10th of image dimensions).

- **Training & Validation**

- **Five-Fold Cross-Validation:**

- Divide data into five subsets.
- Train on 4 subsets, test on 1
- Rotate subsets, ensuring no overlap between training and testing data.

Datasets



(a) Forest



(b) Logyard



(c) Logs



(d) Disc



(e) UruDendro3



(f) Kennel

Collection	Number of images	Specie
UruDendro2	119	<i>Pinus taeda</i>
UruDendro3	9	<i>Gleditsia triacanthos</i>
Kennel	7	<i>Abies alba</i>
Forest	57	<i>Douglas fir</i>
Logyard	32	<i>Douglas fir</i>
Logs	150	<i>Douglas fir</i>
Discs	208	<i>Douglas fir</i>

582

Results

Average over each dataset

Lower the
better

	UruDendro2	UruDendro3	Kennel	Forest	Logyard	Logs	Discs
LFSA (21)	1.03 (0.85)	1.46 (0.97)	0.42 (0.18)	0.80 (0.36)	1.02 (0.62)	0.80 (0.46)	0.72 (0.43)
ACO (3)	2.23 (6.64)	4.52 (11.96)	0.2 (0.06)	0.24 (0.24)	0.60 (1.11)	0.46 (0.45)	0.24 (0.35)
APD-PCL	0.42 (0.34)	0.74 (0.54)	0.19 (0.10)	0.81 (0.98)	0.82 (0.84)	0.52 (0.47)	0.46 (0.57)
APD	1.02 (2.45)	0.55 (0.30)	0.14 (0.06)	0.22 (0.18)	0.35 (0.17)	0.29 (0.33)	0.26 (0.42)
APD-DL	0.55 (1.45)	0.13 (0.06)	0.14 (0.07)	0.45 (1.85)	0.52 (1.29)	0.22 (0.46)	0.23 (0.54)

Results on all the datasets. Normalized errors. We show the mean error and the standard deviation between parenthesis.

Performance Summary

Average over the full dataset (582 samples)

Lower the
better



Method	Mean	Median	Max	FN	Time
LFSA (21)	0.83	0.72	5.03	0	627
ACO (3)	0.79	0.21	36.39	2	918
APD-PCL	0.52	0.34	4.33	0	2339
APD	0.42	0.19	15.44	0	784
APD-DL	0.33	0.14	13.91	3	209

Results of all the methods over the whole set of images, i.e., merging all collections.
Normalized errors, number of false negatives, and execution time in milliseconds.

Qualitative results

Purple, LFSA; Red, ACO; Blue, APD; Yellow, APD-PCL and Green, APD-DL

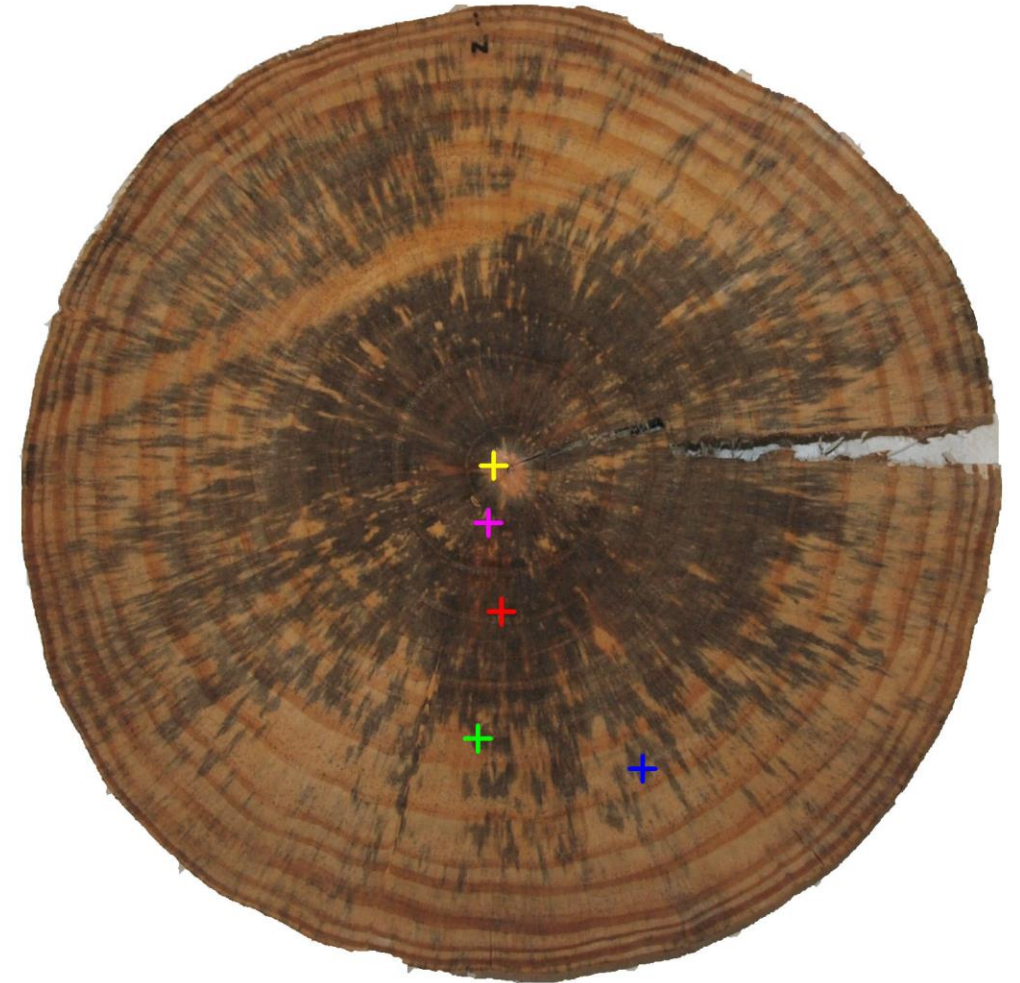
Sample with fungal degradation. APD-PCL is the best method



Qualitative results

Purple, LFSA; Red, ACO; Blue, APD; Yellow, APD-PCL
and Green, APD-DL

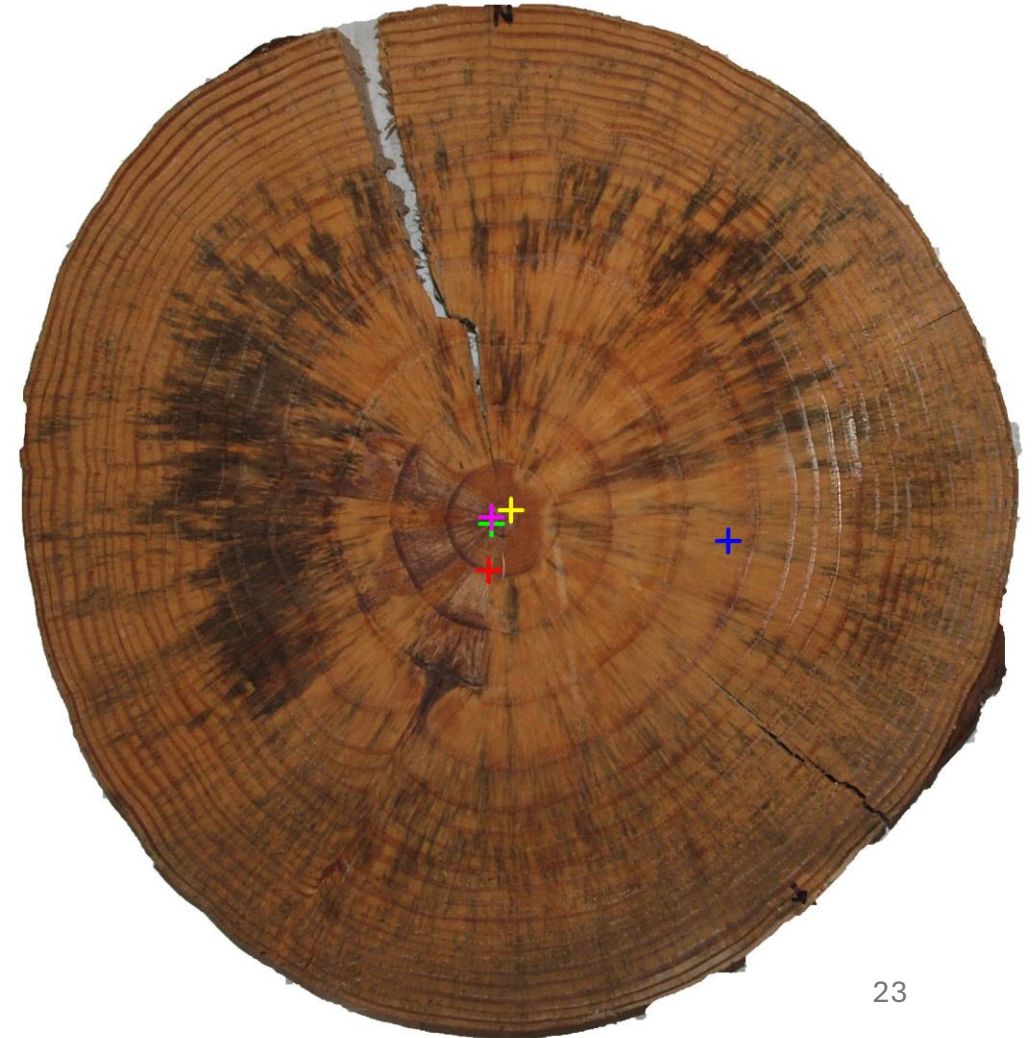
Sample with fungal degradation. APD-PCL is the best method



Qualitative results

Purple, LFSA; Red, ACO; Blue, APD; Yellow, APD-PCL
and Green, APD-DL

Sample with fungal degradation. APD-PCL is the best method



Conclusions

- Proposed a comparative study of classic and machine learning-based methods for pith detection.
- Introduced the **UruDendro Dataset**, enhancing the community's ability to benchmark and develop new methods.
- Methods were assessed over different species, acquisitions condition and perturbations.
- APD method outperformed the YoloV8 model in the datasets Kennel, Forest and Logyard

Thanks

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