Uncertainty-driven Forest Predictors for Vertebra Localization and Segmentation

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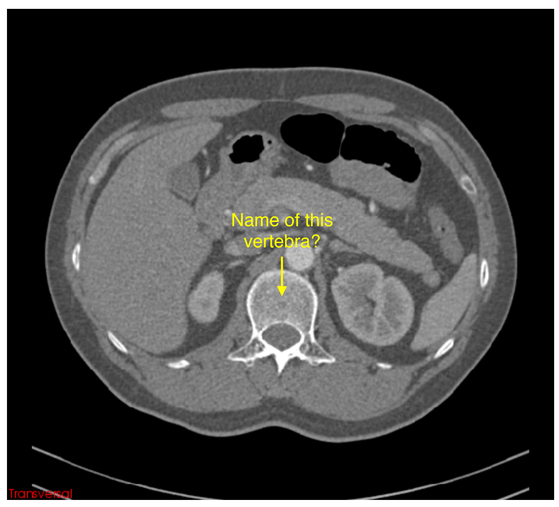
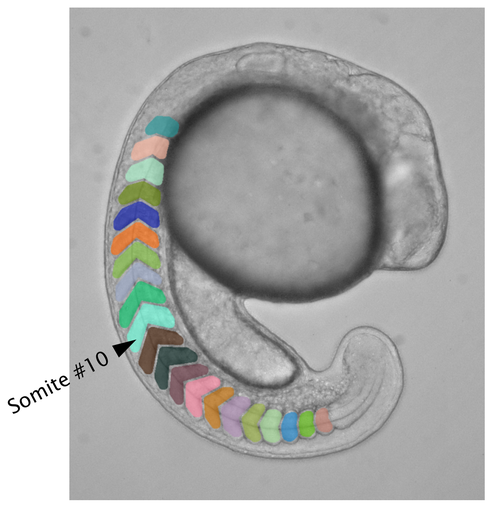
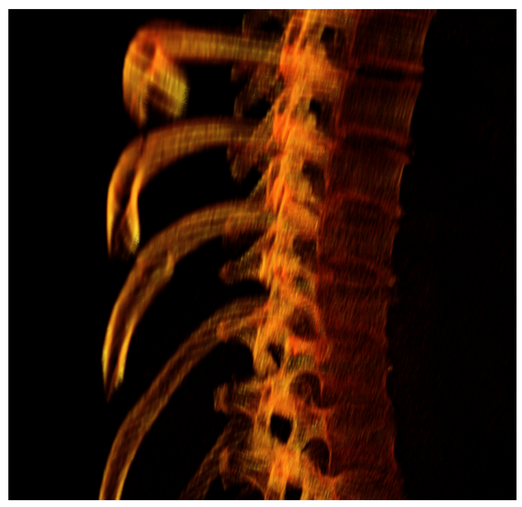
1. Vertebra localization and segmentation are important tasks in medical and bio-imaging



Clinical Motivation:
- Guided visualization and navigation
- Population analysis

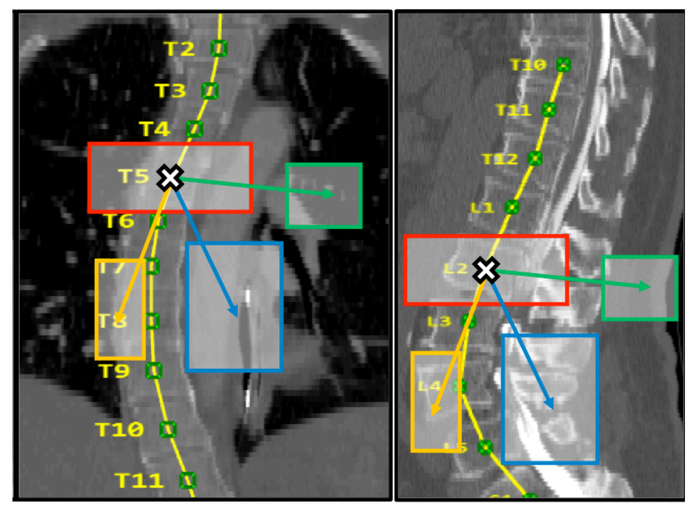


Research Motivation:
- Developmental expression profiles
- Population analysis
- Screening



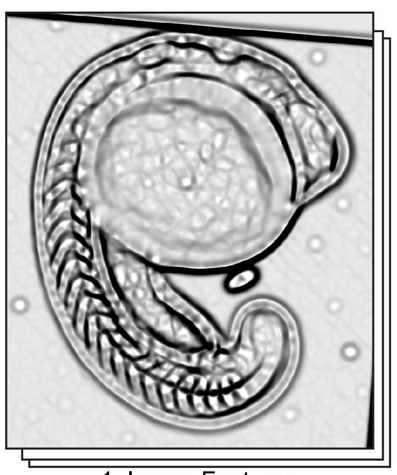
Challenges:
- Repetitive nature of structures
- Small field of view
- Variability of normal anatomy, pathologies

2. Discriminating Vertebrae

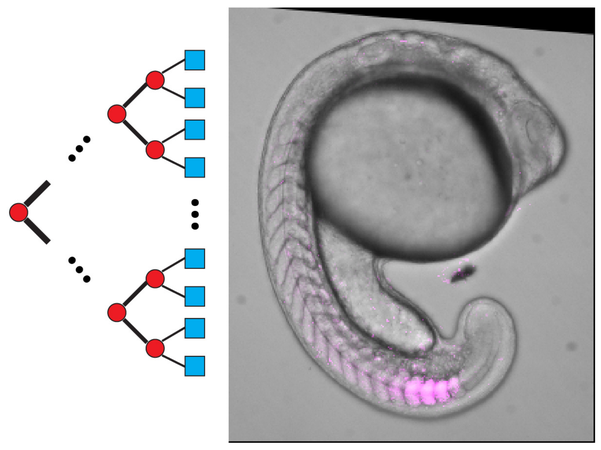


Random Forest with Contextual Features [1]:
- Learns features that distinguish object classes
- Contextual features capture anatomical model

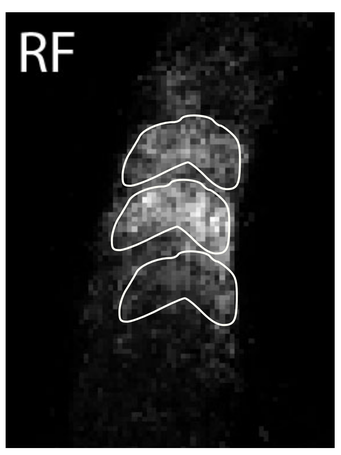
3. Standard Localization and Segmentation Pipeline based on Random Forest (RF) Classifier and Vertebra Constellation Model



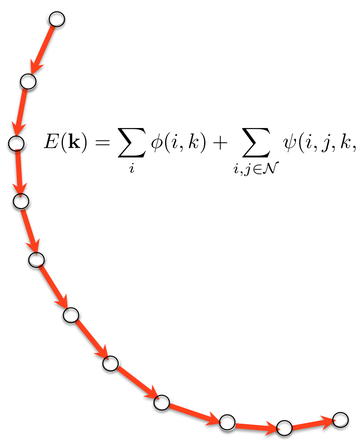
1. Image Features



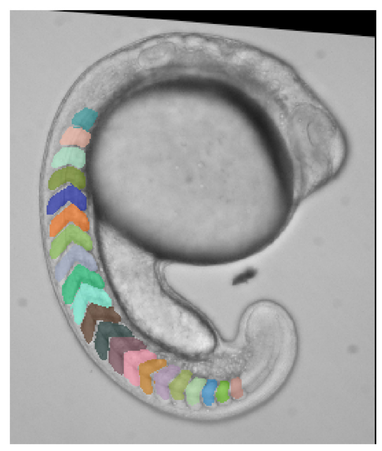
2. Probability maps output by Random Forest Classifier



3. Candidate Segmentations



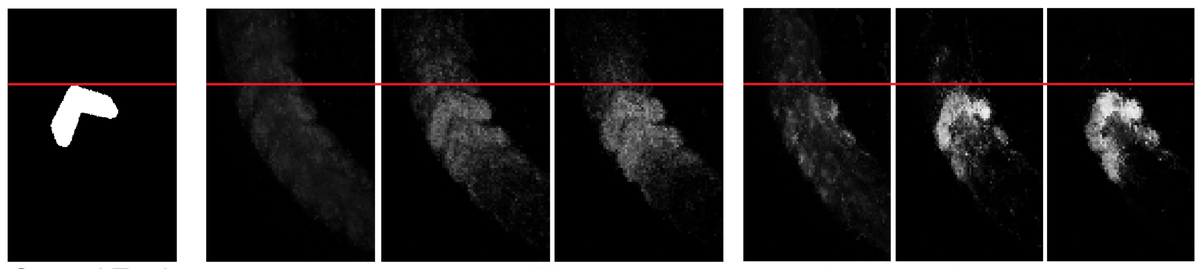
4. Inference



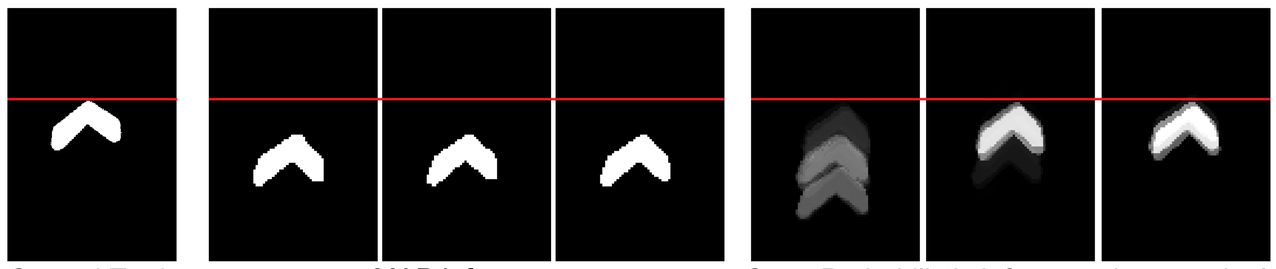
Result: Pixel Labelling

Better Probability Maps with Cascaded Classifiers

Our Contribution: Model-based "Smoothing" by Probabilistic Inference

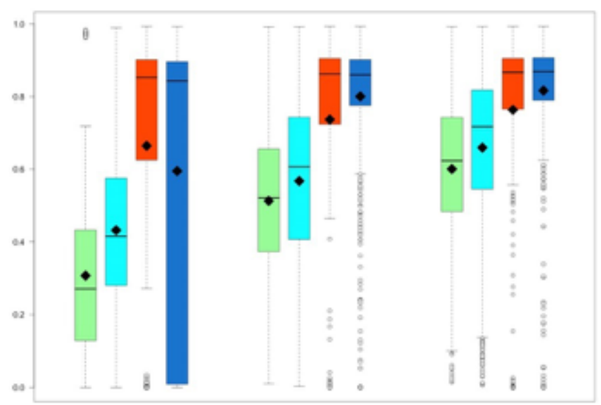


Ground Truth | Auto-context [2] | Geodesic Smoothing [3]



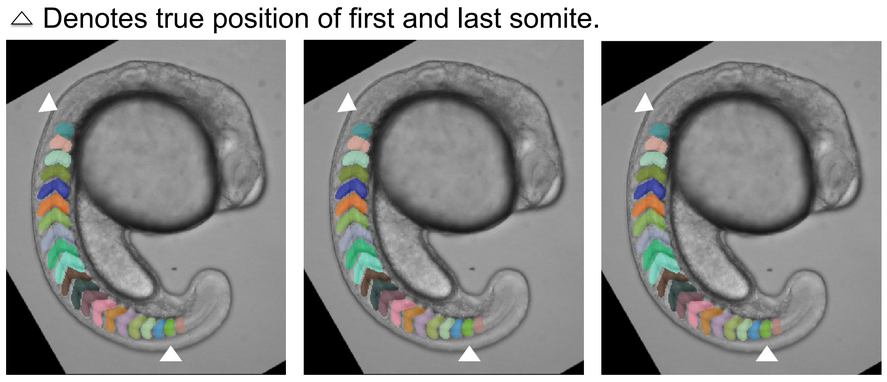
Ground Truth | MAP inference | Ours: Probabilistic inference, i.e. marginals

4. Evaluation: 32 Zebrafish Images

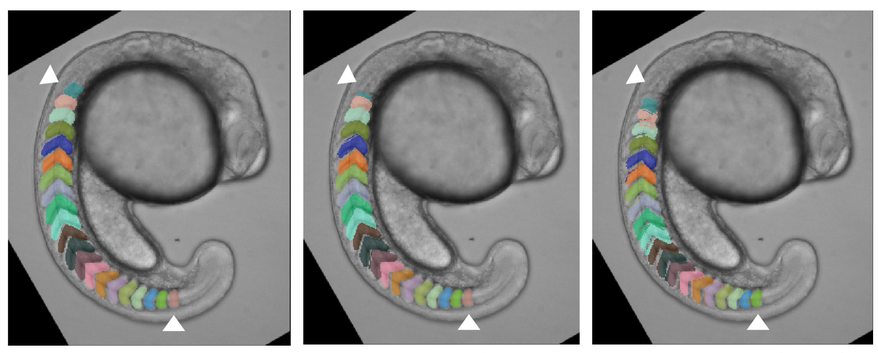


5. RF Cascade with prob. inference 'rescues' poor early predictions, MAP inference does not

△ Denotes true position of first and last somite.



MAP Level 1 | Level 2 | Level 3



Ours Level 1 | Level 2 | Level 3

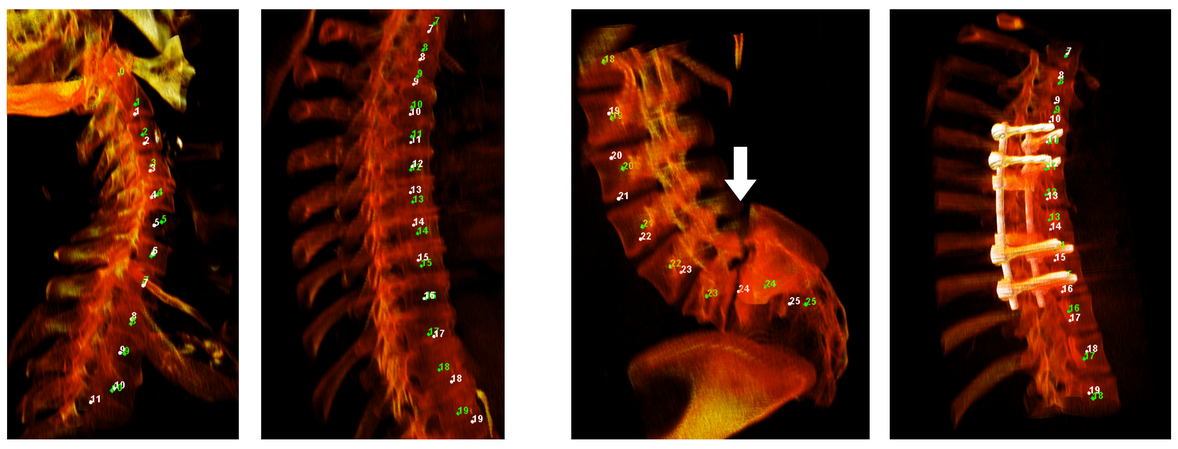
	Dice Score	Variable Importance
Auto-context	60 % (±20)	-
GeoF	66 % (±22)	-
MAP	76 % (±27)	24 %
Ours	**82** % (±**18**)	**55** %

Marginal Features outperform Auto-context, GeoF, and MAP

6. Evaluation: 121 Human Spine CTs

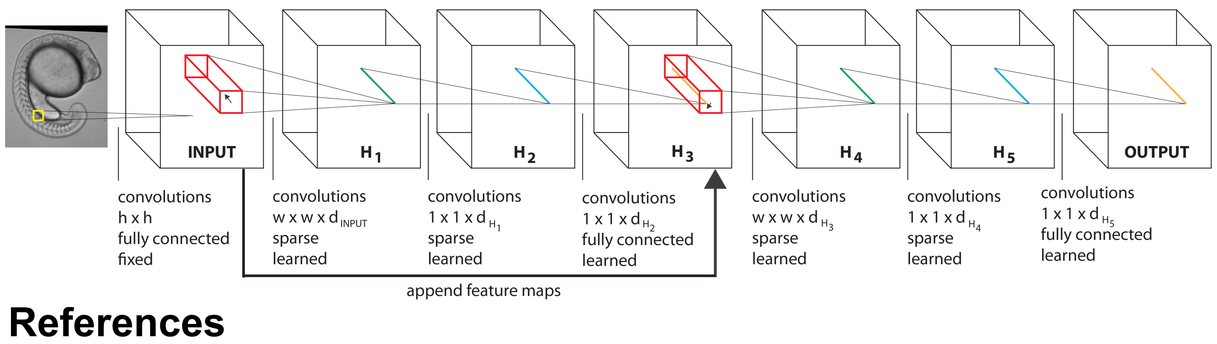
Compared to Glocker et al. [1]:
+12 % True Positive Rate, +10 % Precision

True Pos. Rate	Level 1	Level 2
Auto-context	0.66	0.68
MAP	0.69	0.74
Ours	0.69	**0.75**



Good cases | Bad cases

7. Taking it further: Mapping cascaded RF to a deep CNN [4]



References

[1] Glocker, B., Zikic, D., Konukoglu, E., Haynor, D.R., Criminisi, A. Vertebrae localization in pathological spine CT via dense classification from sparse annotations. In MICCAI 2013.
[2] Tu, Z. Auto-context and its application to high-level vision tasks. In CVPR 2008.
[3] Kontschieder, P., Kohli, P., Shotton, J., Criminisi, A. Geof: Geodesic forests for learning coupled predictors. In CVPR 2013.
[4] Richmond, D.L., Kainmueller, D., Yang, M.Y., Myers, E.W., Rother, C. Relating Cascaded Random Forests to Deep Convolutional Neural Networks for Semantic Segmentation. arXiv.org 2015.