Fully automated and Robust Analysis Technique for Popliteal Artery Vessel Wall Evaluation (FRAPPE) using Neural Network Models from Standardized Knee MRI

Li Chen
Vascular imaging lab
University of Washington

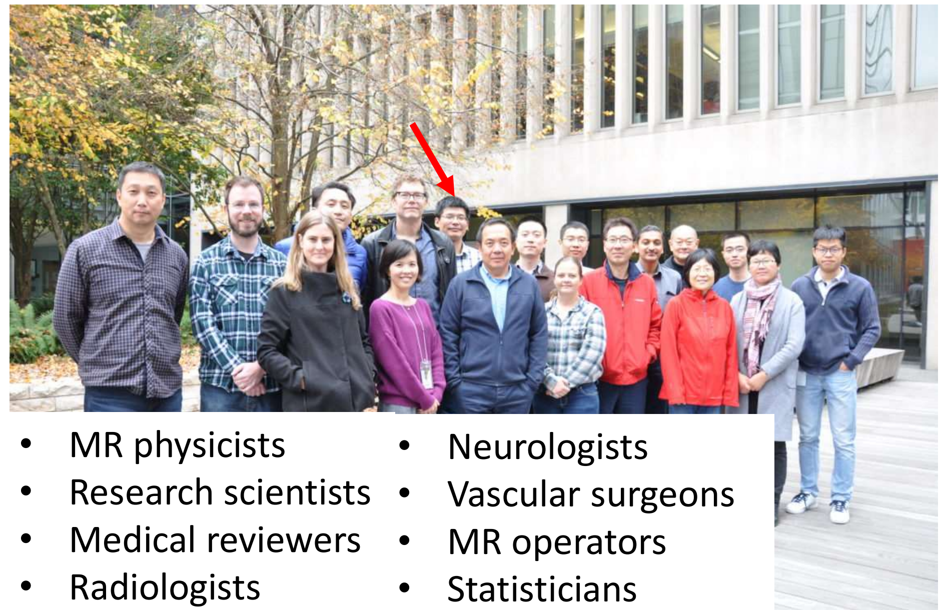
UNIVERSITY *of* WASHINGTON

Introduction of myself and my groups

A 5th year Electrical Engineering PhD student receiving funding from a Radiology lab

Engineering students with specialty in each technical area

Information Processing Lab
Department of Electrical and Computer Engineering
Interests: Machine learning, computer vision



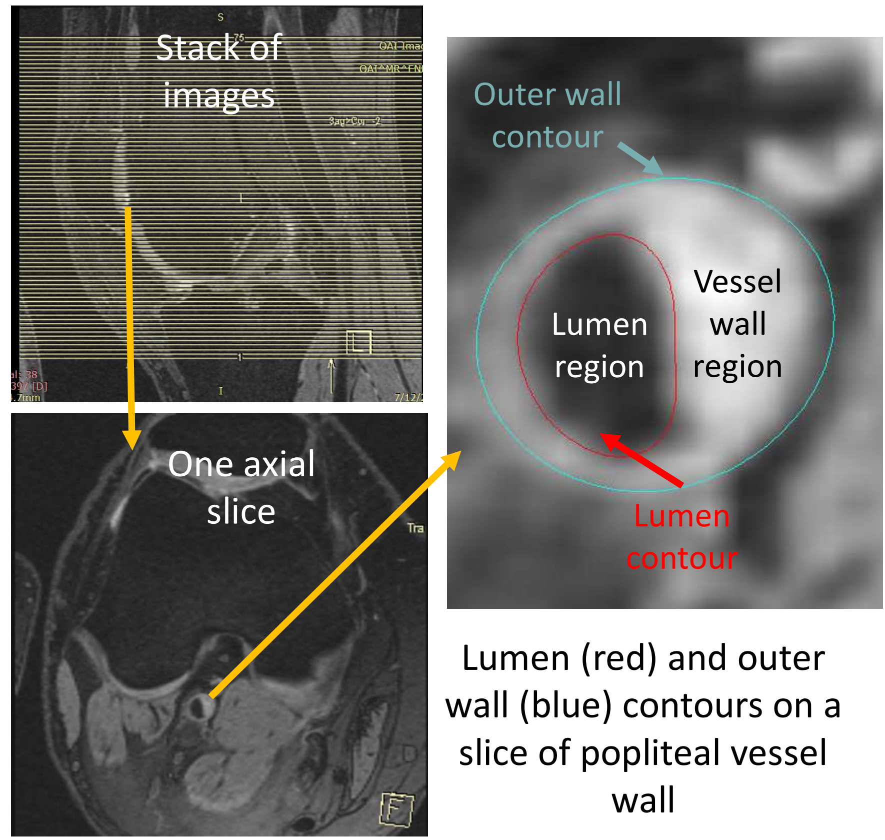
- MR physicists
- Research scientists
- Medical reviewers
- Radiologists
- Neurologists
- Vascular surgeons
- MR operators
- Statisticians

Vascular Imaging Lab
Department of Radiology
Interests: Vascular disease, medical research

Hidden treasure for vessel wall research from OAI

> The Osteoarthritis Initiative (OAI) Study:
  - Originally for osteoarthritis research
  - The 3D DESS sequence suitable for vessel wall studies
  - 4796 subjects, 8 time points, 3.5M images
  - Atherosclerosis: a systemic disease

> Manual review of MRI in OAI dataset is impossible
  - ~4 hours/scan, ~67 years in total



Lumen (red) and outer wall (blue) contours on a slice of popliteal vessel wall

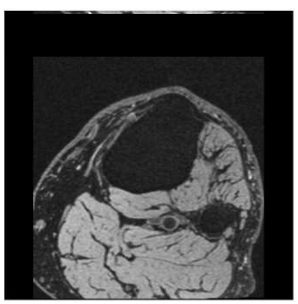
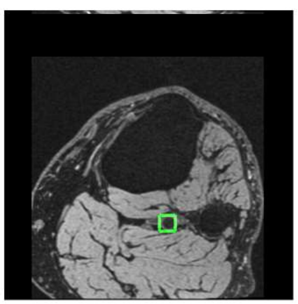
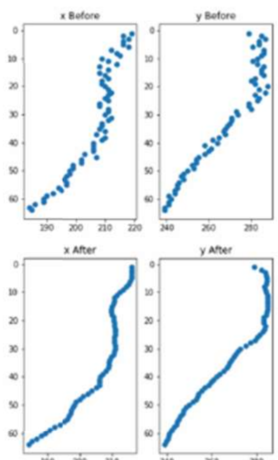
OAI: https://nda.nih.gov/oai/

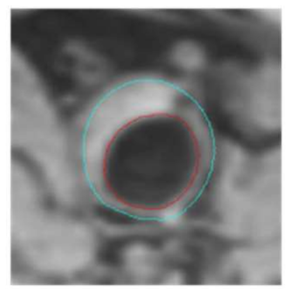
From Liu, et. al, Arterioscler Thromb Vasc Biol. 2019

FRAPPE: AI solution for OAI analysis

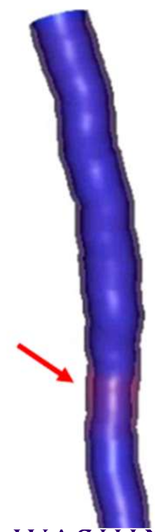
> Locate artery region (<1% image pixel) along slices accurately
> Segment vessel wall regions continuously and smoothly

Original image → Artery detection → Tracklet refinement → Vessel wall segmentation → Feature calculation → Export and display



Max wall thickness:
2.62 mm
Mean wall thickness:
1.46 mm
Vessel wall area:
74.49 mm^2
Lumen area:
36.30 mm^2
......

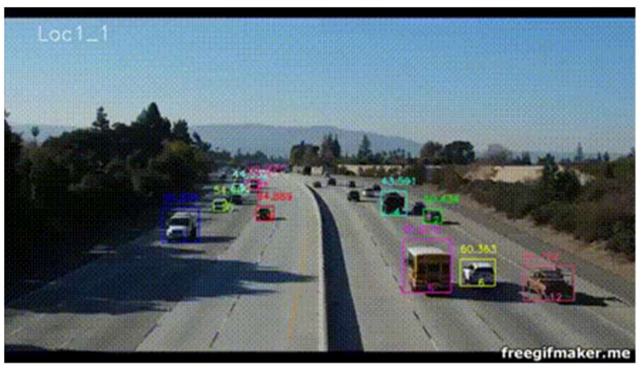


From Chen, et. al, Magn Reson Med, 2020
Chen, et. al, IEEE Access, 2020

Technique for artery localization

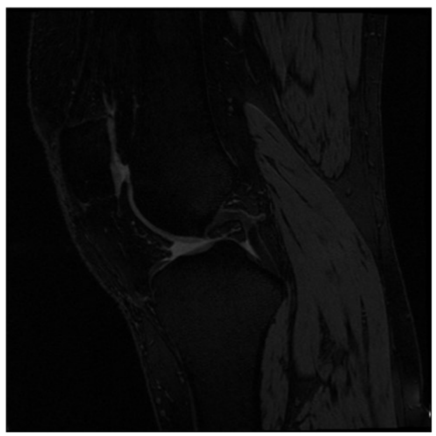
> Time axis in videos ⬄ axial direction in 3D images
  - A neural network [1] for identification of bounding box location

> Tracklet refinement: merge/remove pieces of confident detections



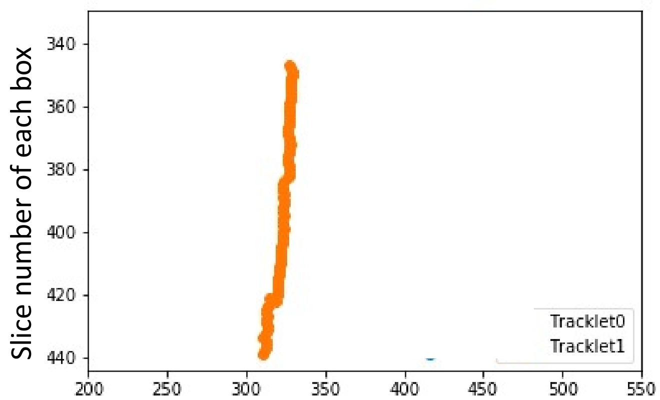
Tracking results of cars (in bounding boxes) using Yolo V2 [1] in NVIDIA AI City Challenge [2]

⬄



Bounding box detection result for a knee scan

Refined tracklets



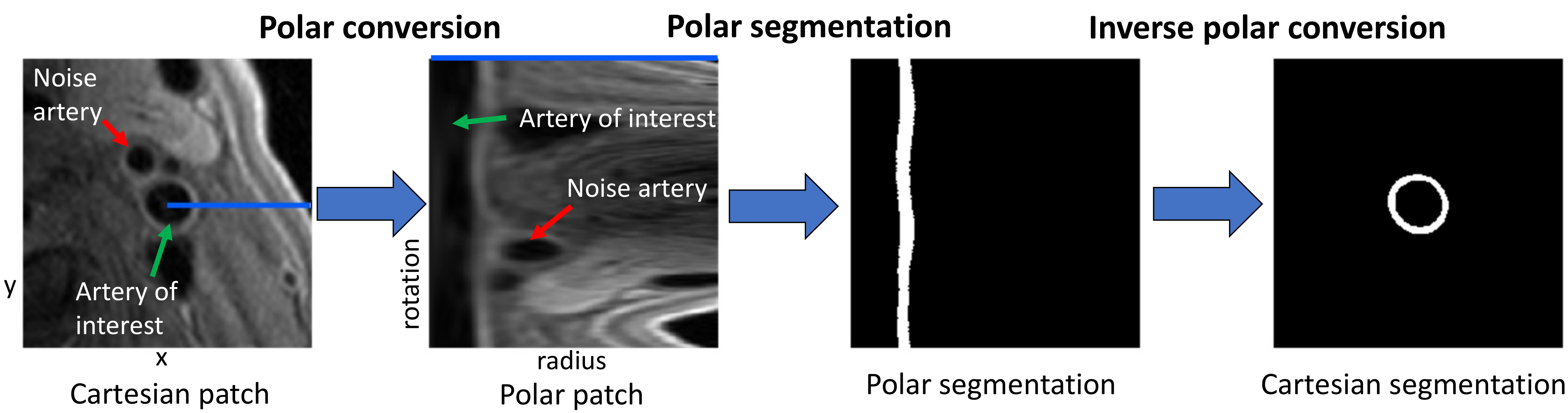
UNIVERSITY of WASHINGTON

[1] Redmon, et. al, CVPR, 2017. [2] Zhen, et. al, CVPR, 2018. [3] Chen, et. al, IEEE Access, 2020

Technique for vessel wall segmentation

> Polar segmentation for vessel wall using neural network
  - Neighboring arteries are different from the artery of interest.
  - Contours are represented as two vertical lines, easy to ensure continuity.

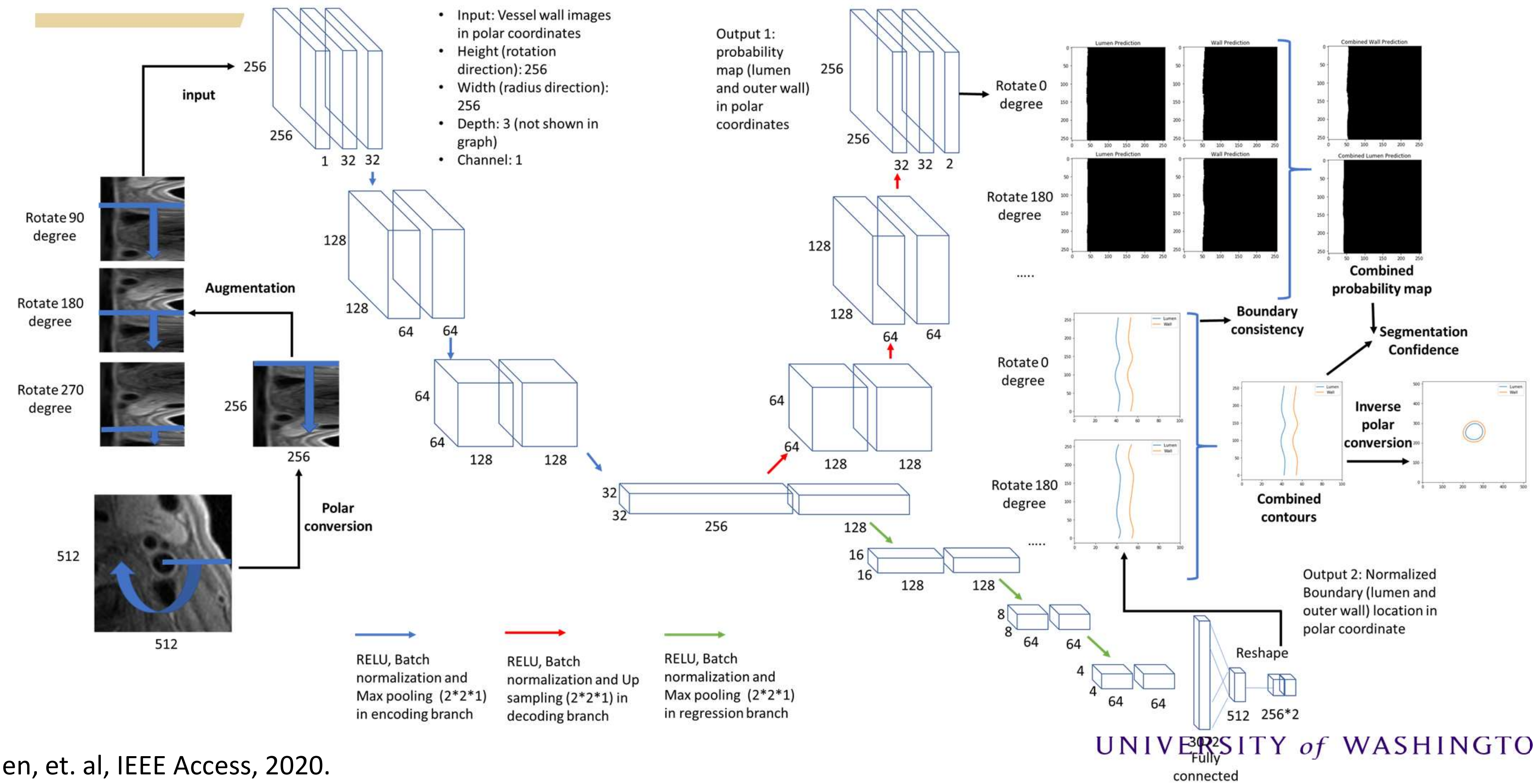
> Transfer learning/active learning from carotid model



Example of polar segmentation in a carotid artery

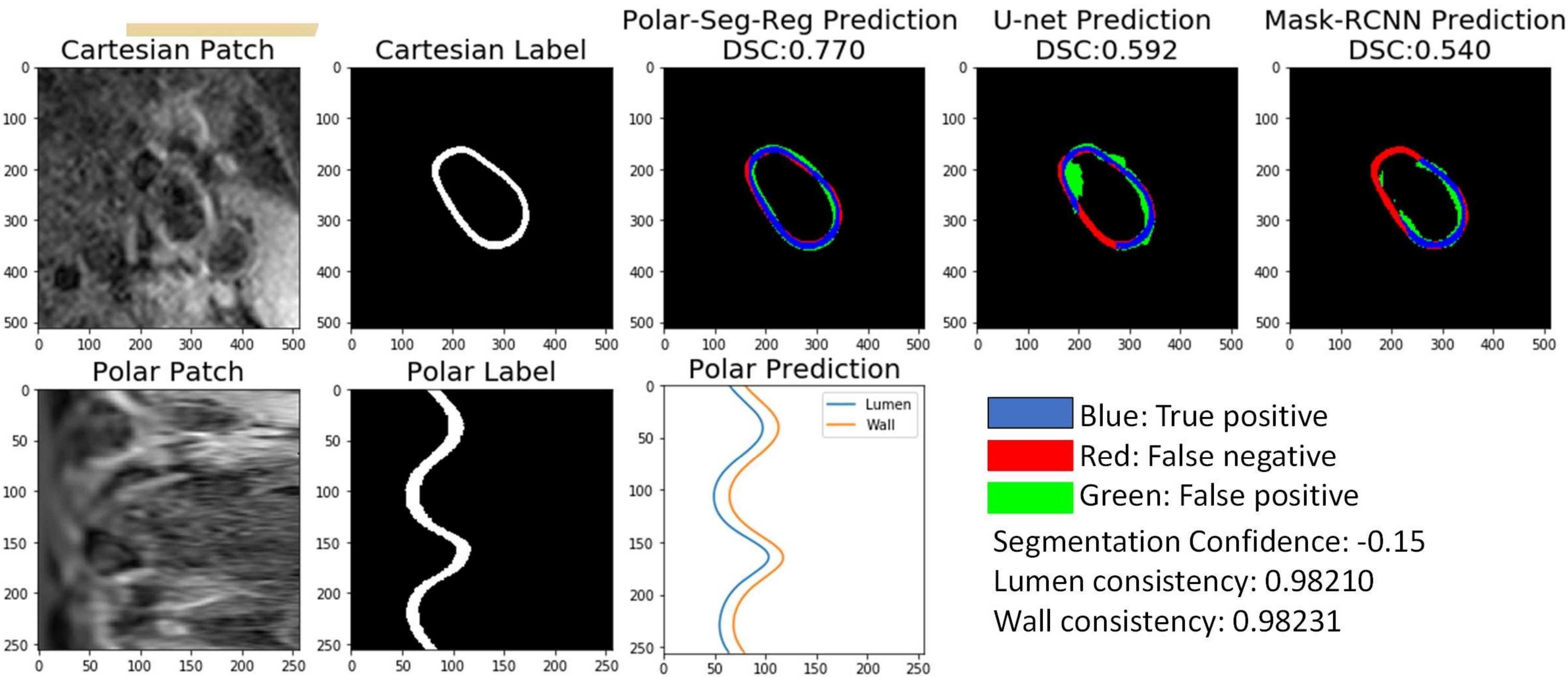
From Chen, et. al, IEEE Access, 2020.

Dual output network for segmentation confidence



From Chen, et. al, IEEE Access, 2020.

Example of polar segmentation result



Blue: True positive

Red: False negative

Green: False positive

Segmentation Confidence: -0.15

Lumen consistency: 0.98210

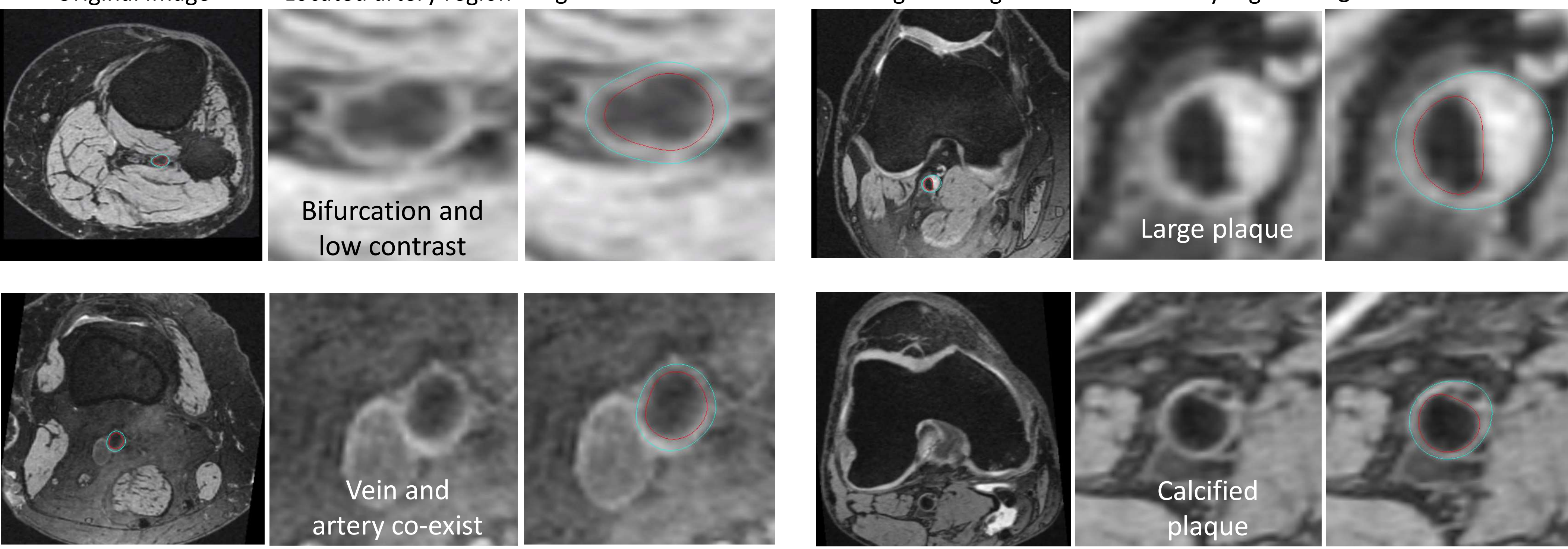
Wall consistency: 0.98231

[1] U-Net: Ronneberger, et. al, arXiv, 2015. [2] Mask-RCNN: He, et. al, ICCV, 2017.

Robust and accurate vessel wall segmentation

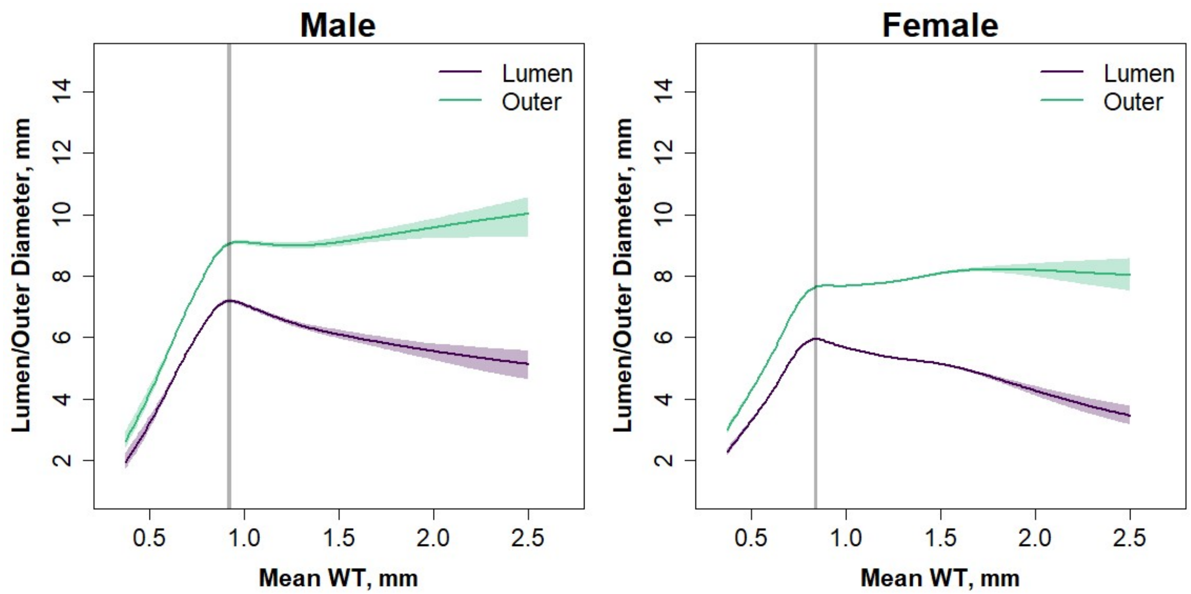
Lumen boundary in red contours
Outer wall boundary in blue contours

Original Image | Located artery region | Segmentation contours | Original Image | Located artery region | Segmentation contours



Discover vessel wall remodeling patterns

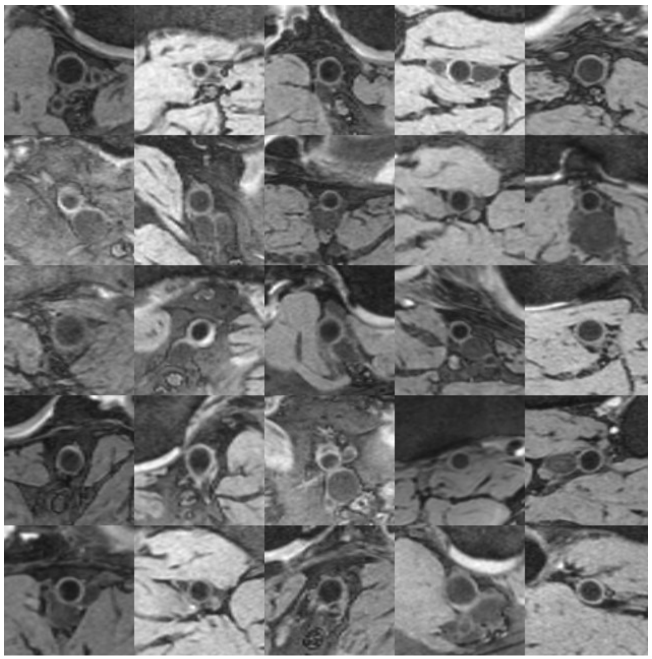
- Averaging from 235,152 and 319,953 images of men and women
- Turning point of 0.92 mm in men and 0.84 mm in women



Spline-smoothed relationships of mean wall thickness with lumen diameter and outer diameter. The shaded regions represent 95% pointwise confidence bands

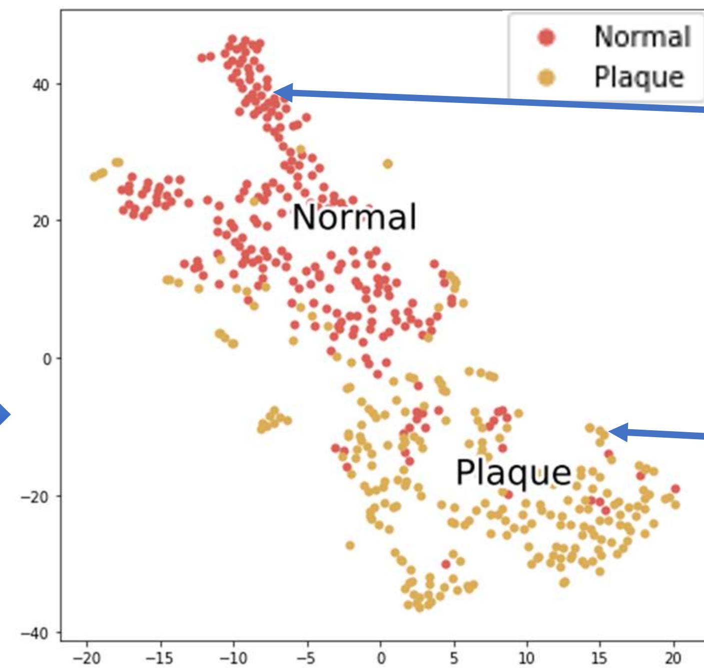
From Canton et al, JAHA, 2021

Intensity pattern features for popliteal artery patches

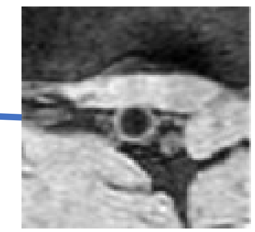


Examples of popliteal artery patches extracted from the center of arteries

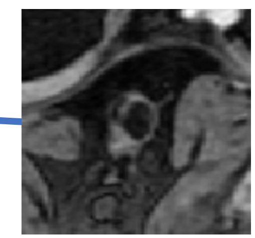
Transfer learning
+
Metric learning



Feature map visualized with t-SNE [1] after transformation using our transfer learning and metric learning method



A sample from the normal cluster



A sample from the plaque cluster

From Chen L, et. al, ISMRM, 2020

[1] Maaten, et. al, Journal of Machine Learning Research, 2008

Awards and Publications

> Awards

- AHA/AWS Prize Competition 2019, sponsored by the Circ: Genomic and Precision Medicine Journal and Amazon Web Services.

> Journal publications

- **Chen L**, et al, Automated Artery Localization and Vessel Wall Segmentation of Magnetic Resonance Vessel Wall Images using Tracklet Refinement and Polar Conversion, IEEE Access, 2020.
- **Chen L**, et al, Fully automated and robust analysis technique for popliteal artery vessel wall evaluation (FRAPPE) using neural network models from standardized knee MRI. Magn Reson Med. 2020 Mar 11.
- Liu W, et al, Understanding Atherosclerosis Through an Osteoarthritis Data Set. Arterioscler Thromb Vasc Biol. 2019 Jun;39(6):1018-1025.
- Hippe DS, et al, Confidence Weighting for Robust Automated Measurements of Popliteal Vessel Wall Magnetic Resonance Imaging. Circ Genom Precis Med. 2020 Feb;13(1)
- Canton G, et al, Atherosclerotic Burden and Remodeling Patterns of the Popliteal Artery as detected in the MRI Osteoarthritis Initiative Dataset. JAHA: Journal of the American Heart Association, 2021

> Conference abstract

- **Chen L**, et al, Visualizing and utilizing the latent features of MR vessel wall images using weakly supervised deep learning analysis workflow. ISMRM 2020 (power pitch)

Acknowledgements

- We acknowledge American Heart Association for supporting this research (18AIML34280043)
- We acknowledge the support of NVIDIA Corporation for donating the Titan GPU

Thanks!

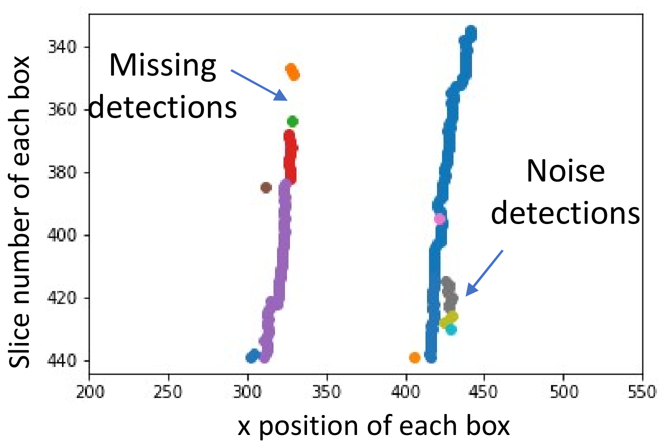
- Questions and answers

> Backup slices

Artery localization: detection + tracklet refinement

Bounding box detection → Tracklet generation → Loss calculation

- Tracklet generation: boxes in neighboring slices with Intersection over Union (IoU) > 0.65



tracklet i

tracklet j

Tail box $TB_i = (x_i, y_i, w_i, h_i, z_i, c_i)$ in tracklet i

Head box $HB_j = (x_j, y_j, w_j, h_j, z_j, c_j)$ in tracklet j

x, y, z: 3D coordinates of box center, w, h: width and height of box

c: confidence score

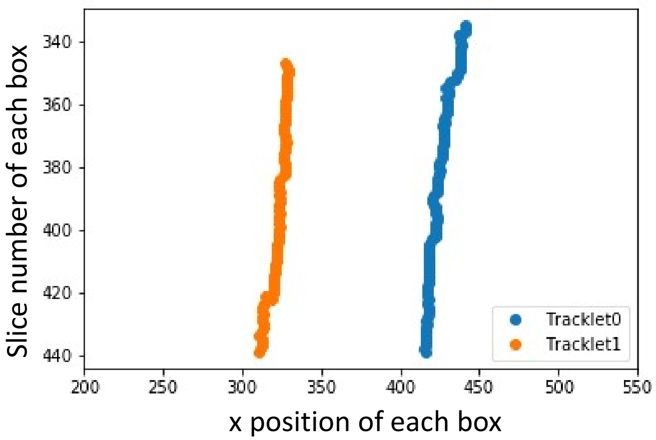
Combined loss $L_{i,j} = a_1 \cdot \max(0, z_j - z_i) - a_2 \cdot IoU\left(TB_i, HB_j\right) + a_3 \cdot (|w_i - w_j| + |h_i - h_j|)$

Weights of $a_{1,2,3}$ decided from validation set

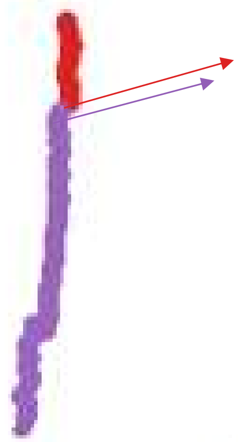
Artery localization: detection + tracklet refinement

Bounding box detection → Tracklet generation → Loss calculation → Tracklet merging → Tracklet removal → Tracklet smoothing

Refined tracklets



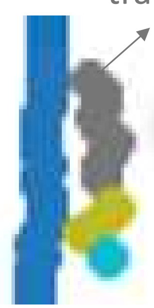
tracklet i



tracklet j

Merge tracklet i and j if $\min(L_{k,j}) = \min(L_{i,k})$
for $k = 1,2,..N$
N: number of tracklets

tracklet r



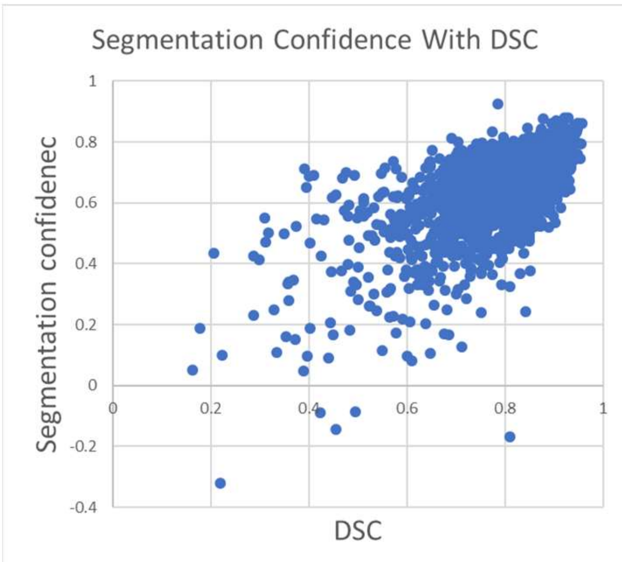
Remove tracklet r if $\frac{1}{M}\sum_M c_r$ below a threshold
M: number of boxes in the tracklet r

Smooth remaining tracklets, using a median filter and a mean filter

Validation of uncertainty scores

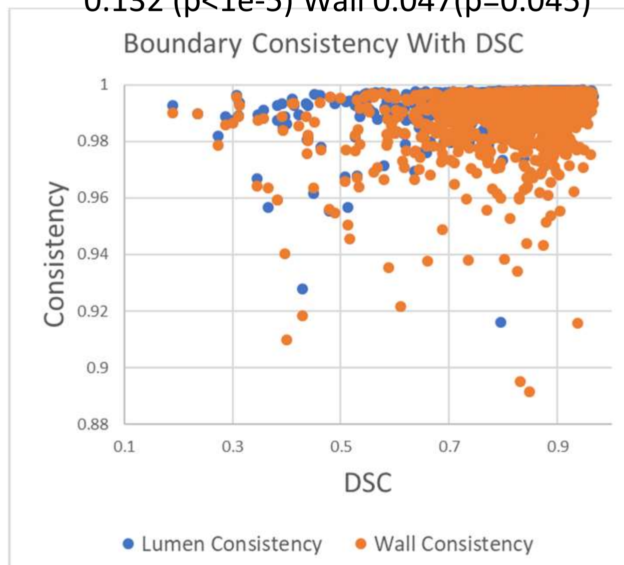
> Uncertainty scores correlates with DSC for vessel wall

Correlation coefficient 0.552 ($p<1e-5$)



Segmentation confidence with DSC^{VW} from the Polar architecture

Partial correlation coefficient: Lumen 0.132 ($p<1e-5$) Wall 0.047($p=0.045$)

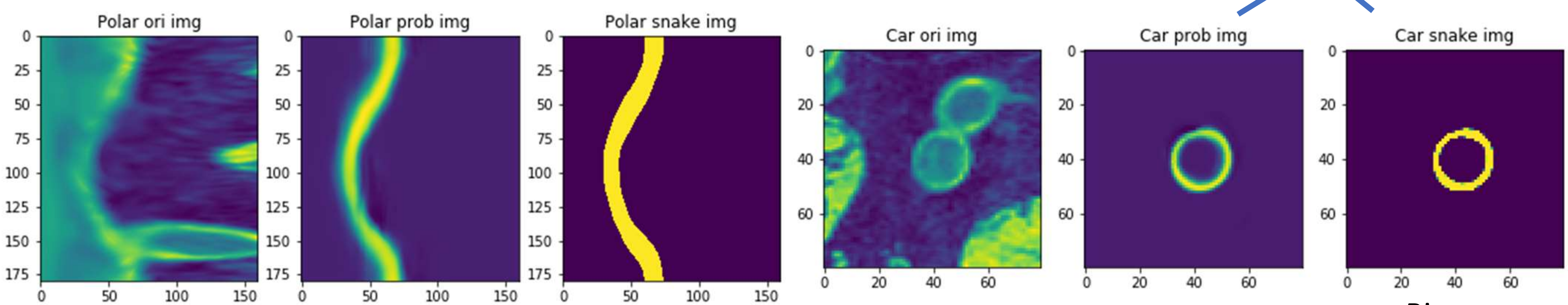


Contour consistency with DSC^{VW} from the Polar architecture

Challenge 2: Vessel wall segmentation

- > A polar segmentation model using convolutional neural network [1]
  - Ensure boundary continuity
  - Avoid impact from neighboring artery wall
- > Confidence score available [2]

Mean value of probability map inside the mask minus outside the mast as confidence score



Polar transformed original image

Probability map from neural network model

Segmentation refined by Snake

Image patch extracted from centerline

Probability map from neural network model

Binary segmentation image refined by Snake

Polar coordinate system

Cartesian coordinate system

[1] Chen L, et. al, arXiv, 2019 [2] Hippe DS, et al, Circ Genom Precis Med, 2020

Challenge 3: Limited human annotations

> Transfer learning from carotid vessel wall segmentation
  - T1 weighted carotid vessel wall MRI has similar structure and intensity distribution
  - Human annotations are abundant for carotid vessel wall segmentation

> Relatively small dataset for human annotations
  - 25 knee scans labeled by experienced vessel wall image reviewer for development
  - Training: 22 scans (1278 slices), validation: 2 scans (113 slices)

> Carotid + popliteal combined dataset has better training performance

Dataset selection for evaluation

> High-risk group
- Subjects ≥65 years old, history of smoke and hypertension, with BMI≥25 kg/m^2,
- AND have one of the seven risk factors:
- 1) operation to unclog or bypass arteries in legs;
- 2) stroke, transient ischemic attack, blood clot or bleeding in brain;
- 3) heart attack;
- 4) diabetes;
- 5) current smoker;
- 6) BMI≥30 kg/m^2;
- 7) age≥75 years old.

> Low-risk group
- Subjects with less than 55 years old, never smoked, not hypertensive, with BMI less than 25 kg/m^2
- AND have none of the seven risk factors specified for the high-risk group

Dataset selection for evaluation

Phase	Dataset name	#subject /slice	Side	Selection method	Purpose
Technical development	Training set 1	23/1326	Index	Simple random sample	Train the neural network model for artery localization and segmentation
	Validation set 1	2/117	Index		Monitor the training procedure and tune parameters
Fine tuning and validation	Training set 2	225	Index	Stratified random sample so that approximately 33% of subjects were from the high-risk group	Further model tuning in a larger dataset, with reviewer's help to identify mistakes and confirm improvements
	Validation set 2	10/743	Index		Contours drawn by both reviewers to compare quantitatively to decide when to stop tuning. Also assess inter-rater variability
Final evaluation	Test set 1	25/1843	Index		Used for performance evaluation in the quantitative assessment
	Test set 2	225	Index		Used for performance evaluation in the qualitative assessment
	Test set 3	100/7273	Index	Random high-risk group	Used for performance evaluation in the repeatability assessment
	Test set 4	100/7098	Both	Random high/low-risk group	Used for evaluating feature differences between high and low risk subjects

Rigorous validation and assessments for FRAPPE

- Assessment of features accuracy
  - Quantitative assessment
    - Agreement on segmentation Dice (0.79), vascular features (intra-class coefficient (ICC) ranging 0.68-0.99) on 25 scans
  - Qualitative assessment
    - 5-minute questionnaire: identify major errors on 225 scans (1.2% of 14,055 images have noticeable major errors)
- Assessment of features repeatability
  - Features between two scans with short intervals (intra-class coefficient ranging 0.80 to 0.98)

From Chen L, et. al, Magn Reson Med, 2020

FRAPPE output: comprehensive vessel wall features

- Vessel wall feature can be calculated from vessel wall segmentation image

> Thickness features
- Max Thickness
- Min Thickness
- Avg Thickness
- Std Thickness
- Eccentricity ratio

> Area features
- Area Vessel Wall
- Area Lumen
- Area WALL
- Normalized wall index

Potentials for FRAPPE

- Clinical application
  - Vessel wall analysis for each knee scan with no additional cost
  - Screening on peripheral arteries for plaques
- Research application
  - Vessel wall features as new imaging biomarkers for cardiovascular research
    - Vessel wall measurements correlate with existing clinical features collected in the OAI study, such as cardiovascular risk factors, physical exercise, diabetes.
  - Quantify longitudinal changes from vessel wall after image registration
  - Vessel wall remodeling patterns
  - Identify vessel wall image patterns