COMP9993 20T3 Research Project C

Deep Learning for Improved Bronchial Tree Segmentation in CT Images

Student

- Oleg Kufirin, z5216713

Supervisor:

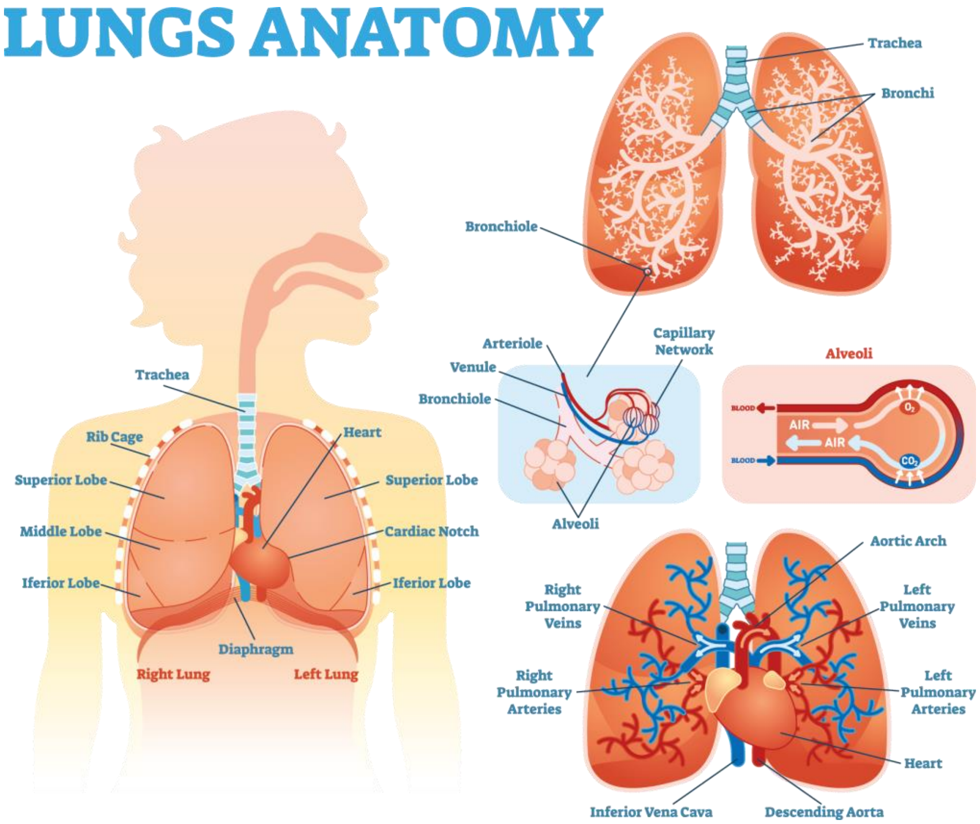
- Erik Meijering

Assessor:

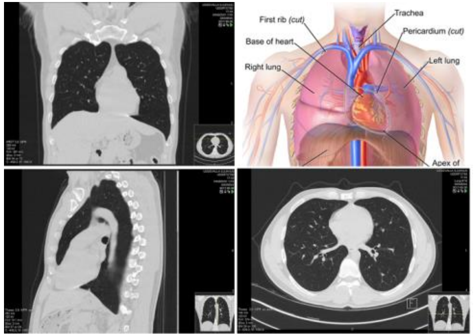
- Daniel Moses

09/12/2020

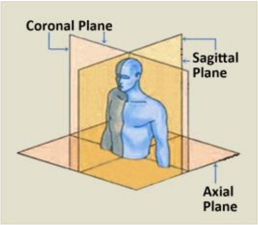
Background information



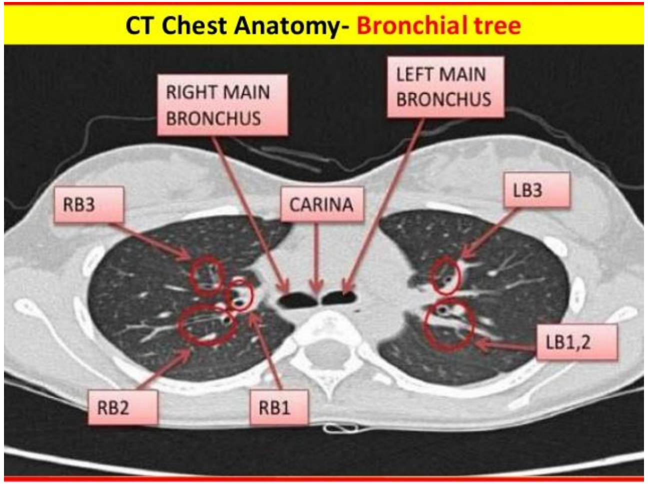
https://www.nras.org.uk/the-effects-of-ra-on-the-lungs



https://glassboxmedicine.com/2020/03/05/automatic-interpretation-of-chest-ct-scans-with-machine-learning/



https://www.ipfradiologyrounds.com/hrct-primer/image-reconstruction/



https://www.slideshare.net/feezone/ct-chest-fundamentals

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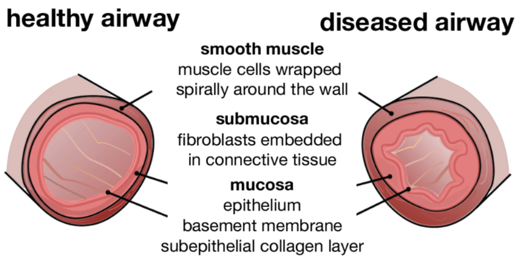
Motivation

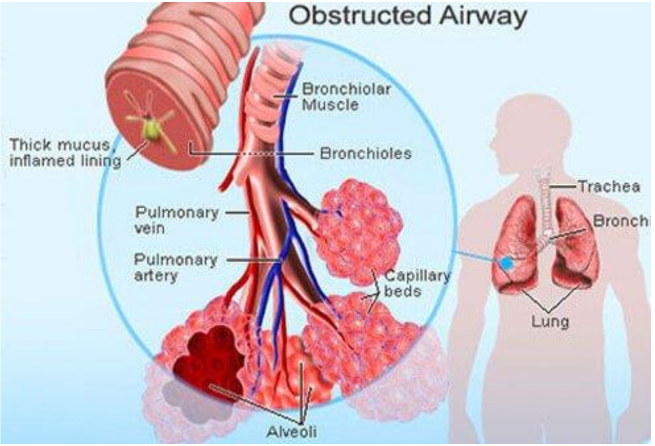
Top 5 Lung Diseases That Affect the Airways:

- Asthma
- Bronchitis
- Emphysema
- COPD (Chronic Obstructive Pulmonary Disease)
- Cystic Fibrosis

+ COVID-19

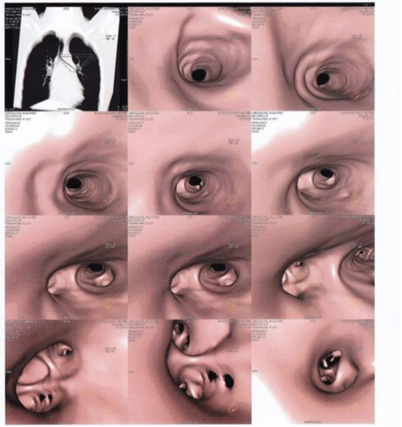


https://www.researchgate.net/figure/Schematic-of-the-airway-wall-Small-airways-consist-of-three-distinct-layers-the-mucosa_fig1_261018942



https://www.onhealth.com/content/1/asthma_lung_inflammation

Virtual bronchoscopy



https://www.researchgate.net/figure/Picture-disclose-virtual-bronchoscopy-in-patient-with-tracheal-web_fig2_309770802

Overview of the baseline method

Computerised Analysis of the Bronchovascular Anatomy of the Lung on Multidetector CT Studies (D. Moses, 2018)

Central Bronchial Tree Segmentation

Isosurface construction and projection

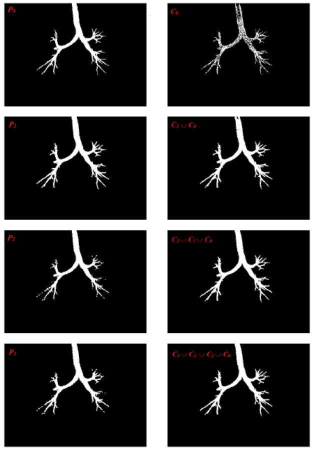


Figure 4-4: Isosurface projection sequence showing P_i and $\{C_i \cup C_{i-1} \cup \ldots \cup C_0\} \subset B_{-850}$ during the first 4 iterations.

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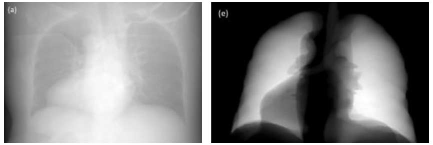
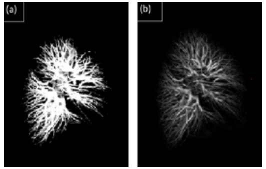
Peripheral Vessel Centerline Identification

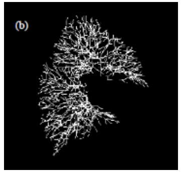
Lung segmentation: thresholding and component analysis



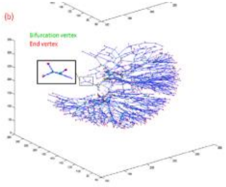
Hessian filtering



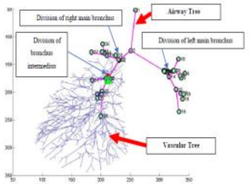
Skeletonisation



Graph Construction

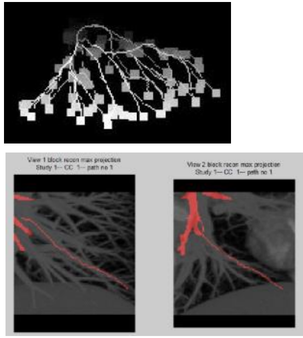


Tree Construction

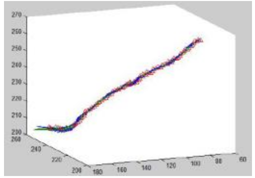


Vector Field: Distance Map + Diameter Map = Composite Map

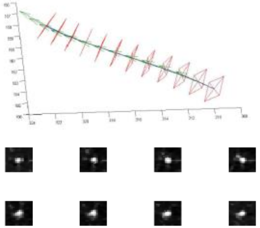
Tracing paths



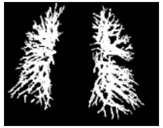
B-spline approximation



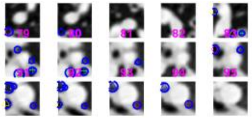
Derivative of the centerline spline: cross –sectional img.



Hough transform, hierarchical clustering for bright circles, stitching, interpolation



Hough transform, hierarchical clustering for dark circles => veins – arteries classification



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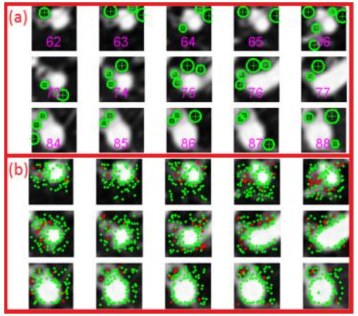
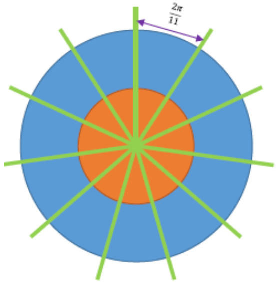
Peripheral Bronchial Tree Identification

Circular Hough transform → Ring filtering → Hierarchical clustering





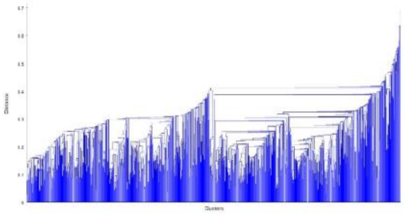
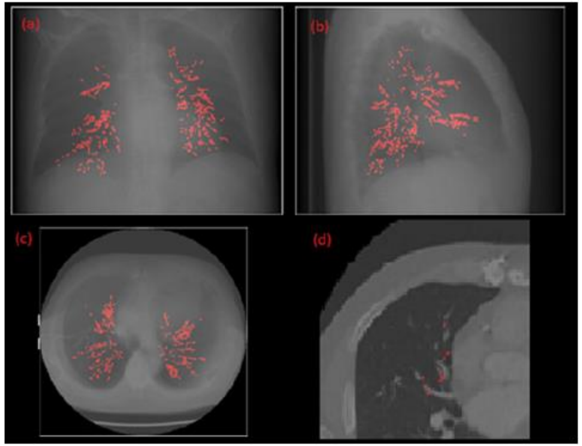
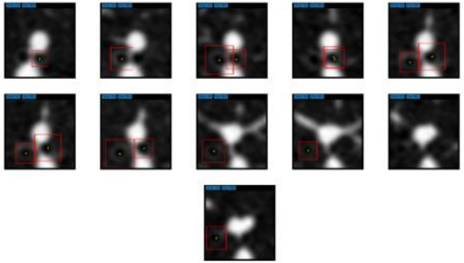


Figure 6-9: Dendrogram showing the results of the hierarchical clustering algorithm with a tolerance of 0.15 and shortest distance measure applied to the training data set with ring filter parameters of β =10 spokes and φ=75 HU.





CNN
(transfer learned)

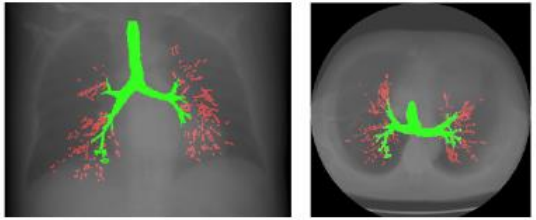
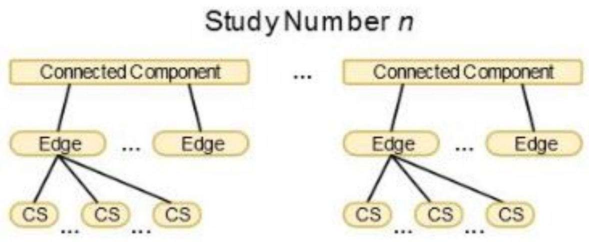


Figure 6-13: Fusion of detected central bronchial tree (green) and peripheral bronchial centre points (red), which shows their spatial relationship within the lung. Note that the peripheral bronchial points extend much more distally than central bronchial tree.

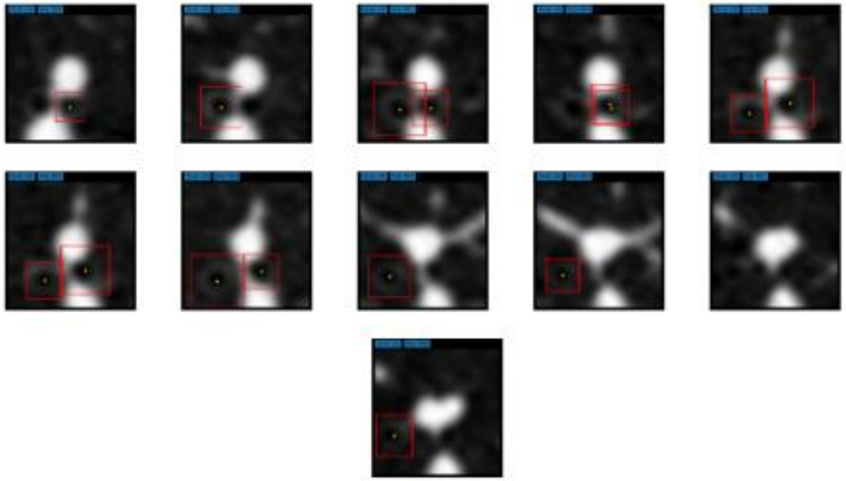
Data set

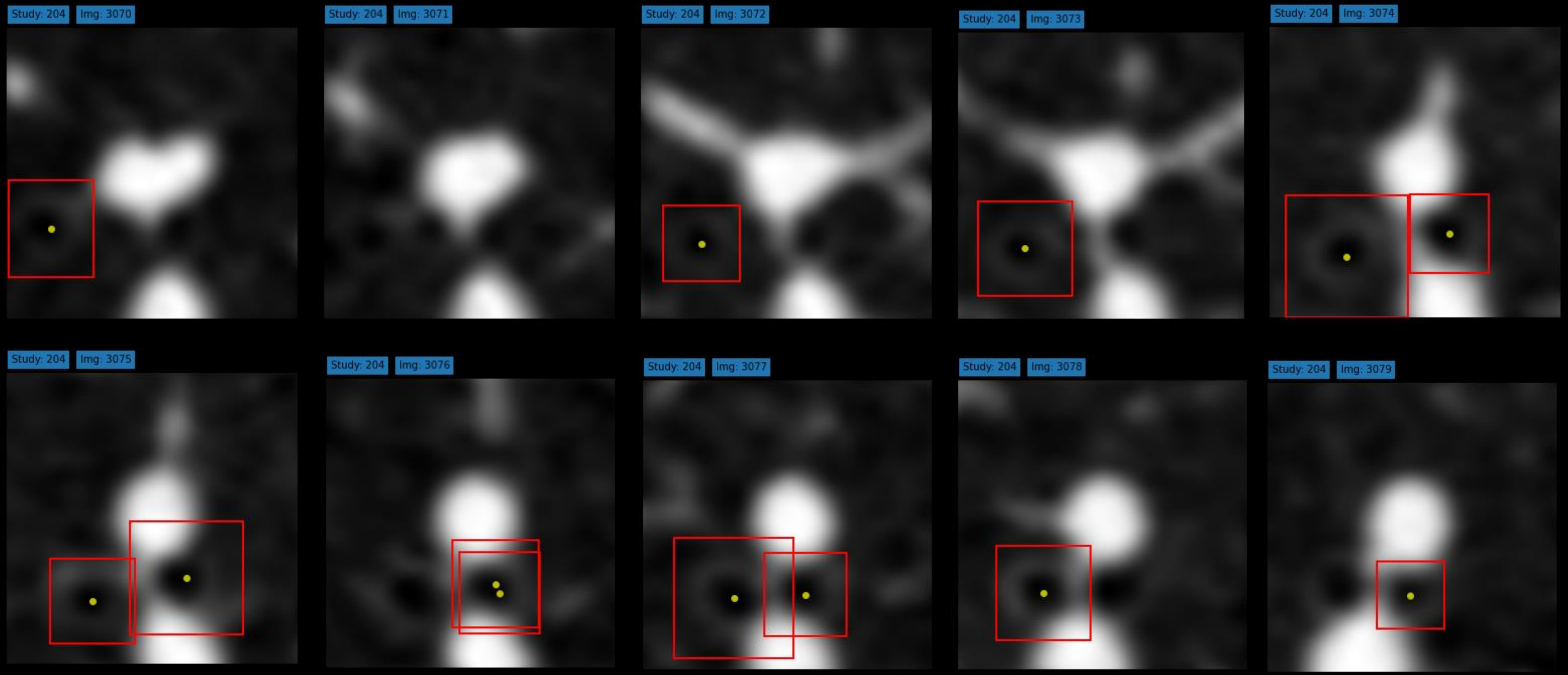
- 11 studies
- 145,575 data files in “.mat” format. Size 161x161 pixels
- Each cross-section is indexed by study no., image no. within a study, connected component no., edge no., cross-sectional image no.
- Global 3D coordinates of each voxel are stored
- Local 2D coordinates of the bounding boxes of located bronchi are stored

Study No	No images	No edges	Edges>50% detection
200	26327	2055	62
201	21652	1749	57
202	7527	470	20
203	9874	738	61
204	14334	1134	134
205	11450	878	163
206	12221	889	41
207	12640	929	27
208	13267	989	72
209	7302	591	80
210	8981	686	44
Total	145575	11108	761

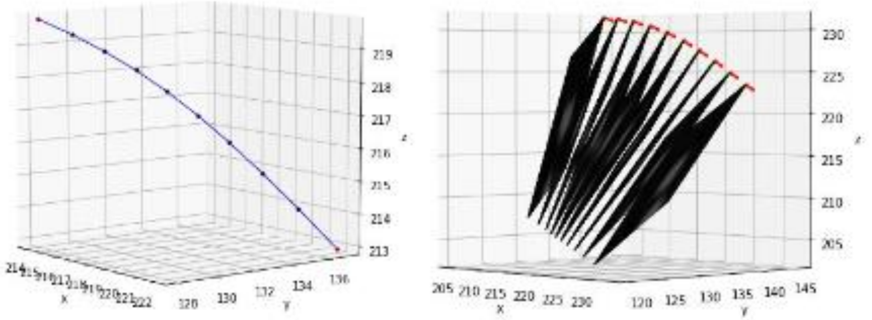


Samples from random edge

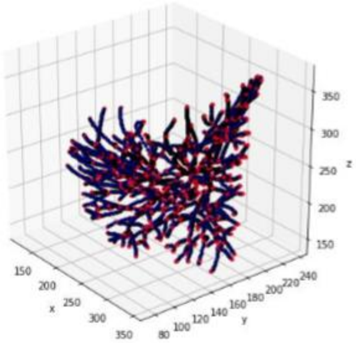



Study: 204
Img: 3070
Study: 204
Img: 3071
Study: 204
Img: 3072
Study: 204
Img: 3073
Study: 204
Img: 3074
Study: 204
Img: 3075
Study: 204
Img: 3076
Study: 204
Img: 3077
Study: 204
Img: 3078
Study: 204
Img: 3079

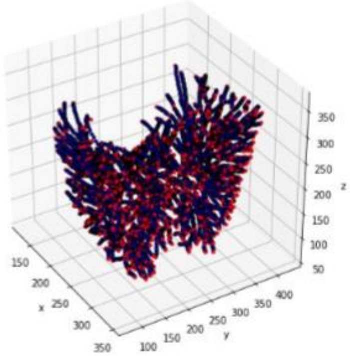
3D visualisation of a vessel edge



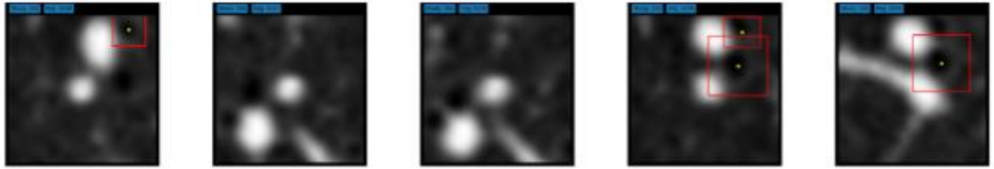
3D con. component

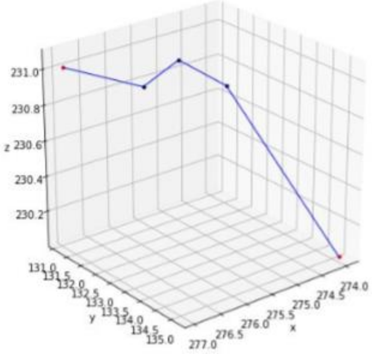


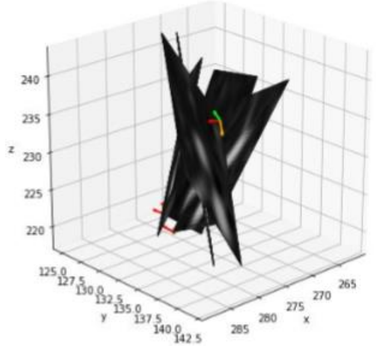
3D study

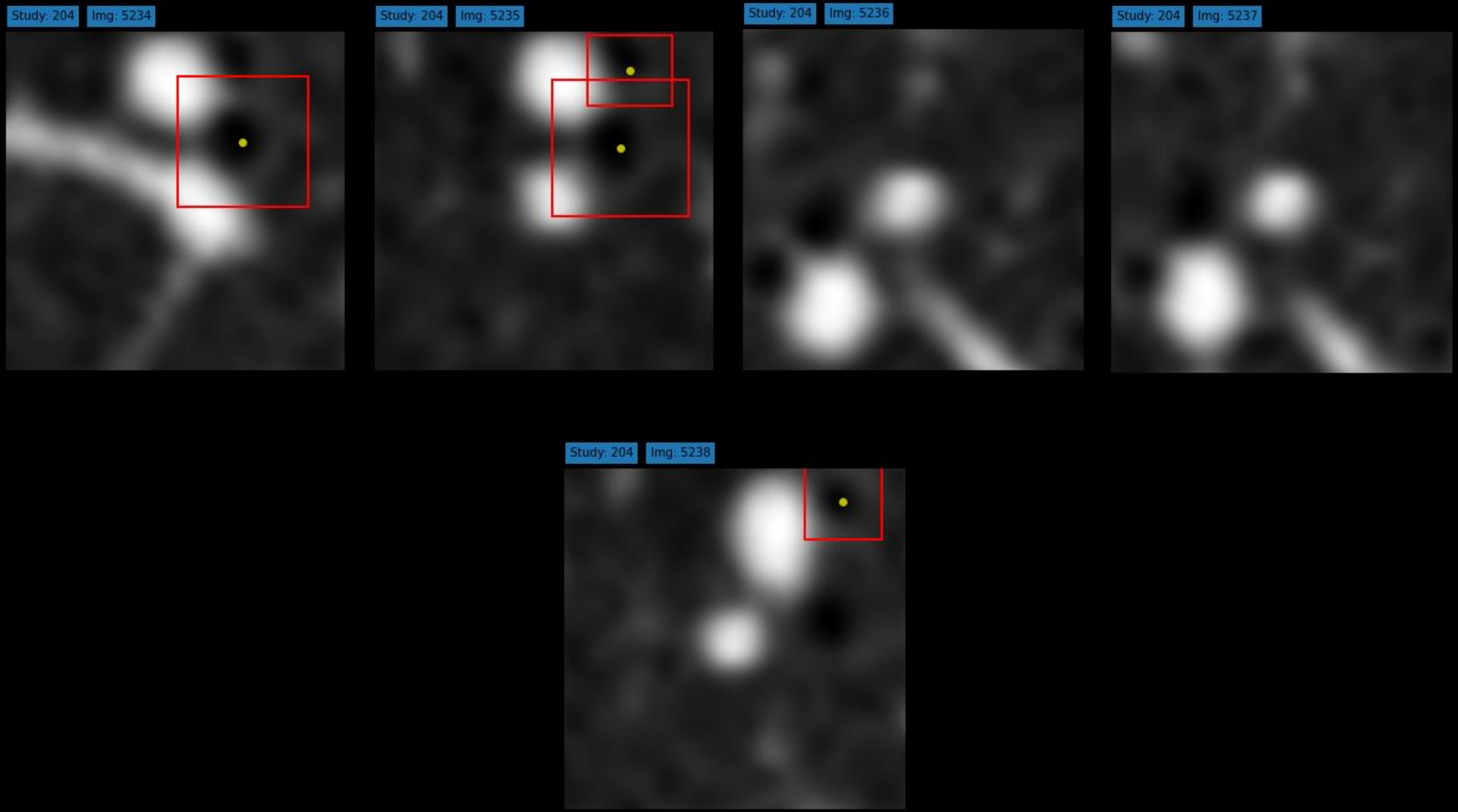


Inconsistent sampling – random flips

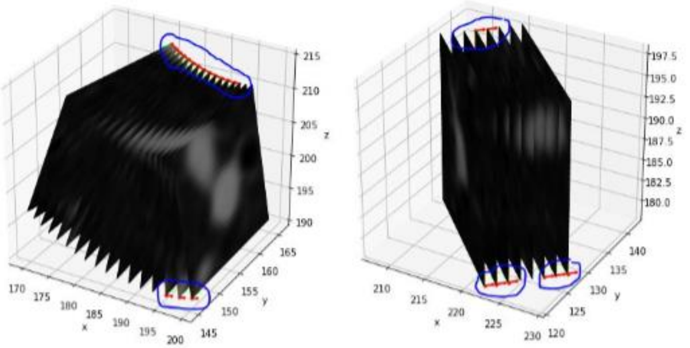


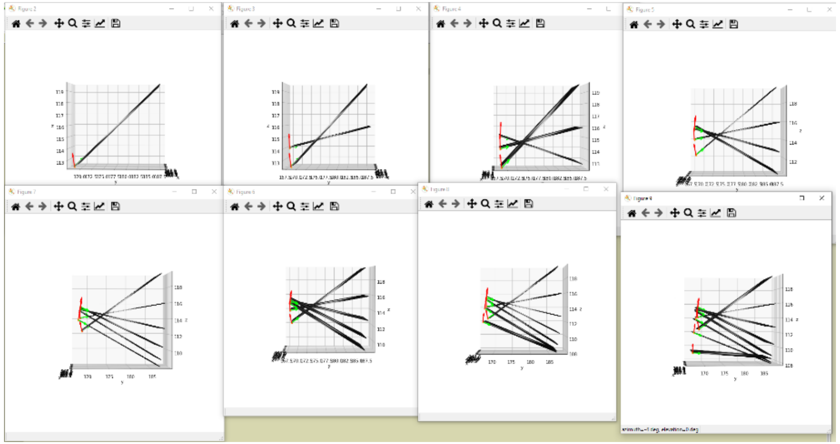




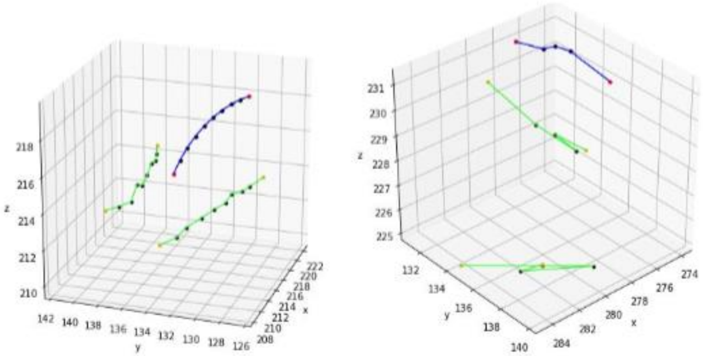

Study: 204
Img: 5234
Study: 204
Img: 5235
Study: 204
Img: 5236
Study: 204
Img: 5237
Study: 204
Img: 5238

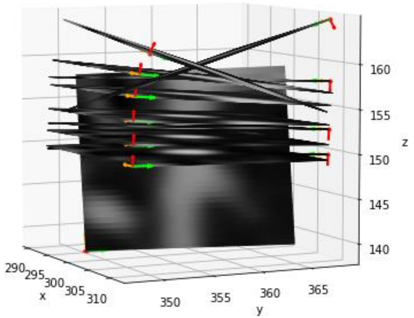
Inconsistent sampling





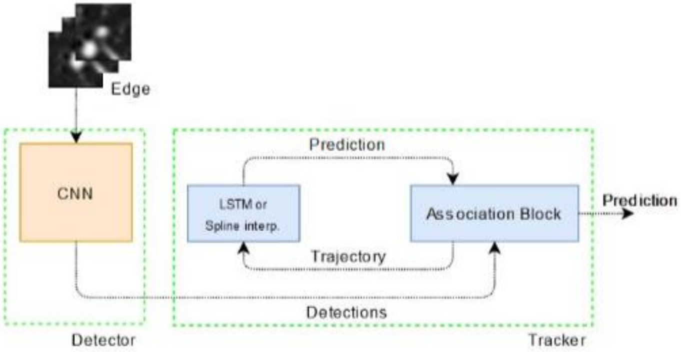
Parallelism of vessels and bronchi





Method

Proposed workflow



Input: sequence of cross-sectional images belonging to one edge

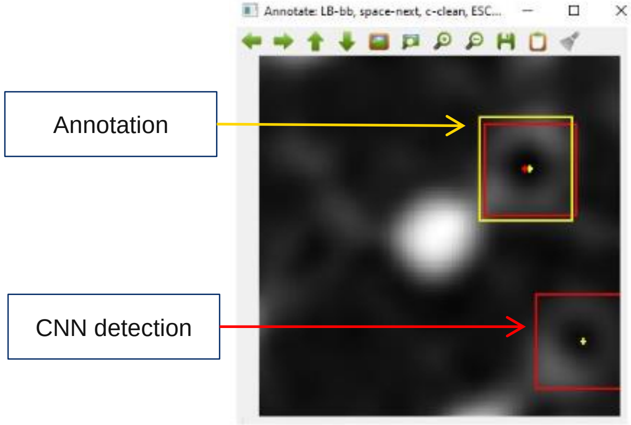
Output: set of bronchi trajectories

CNN: as in the baseline method (transfer-learned SSD)

Association block: coordinate-based mapping (e.g., Hungarian algorithm)

Prediction block: RNN or spline fitting – area of research

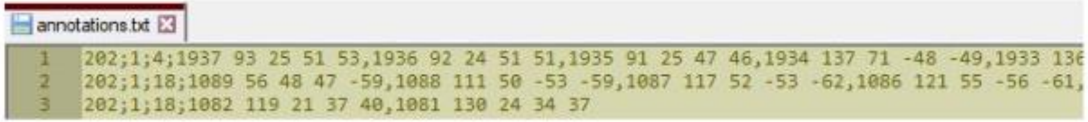
Annotation tool



Labelled edges with > 50% of detection

Annotated 663 edges by the author ~ 2 weeks

Length of annotated segments is ~1 to 30



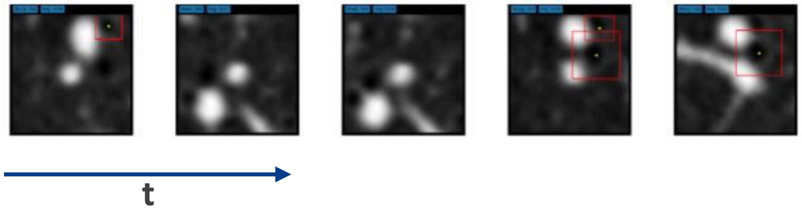
annotations.txt

```
1  202;1;4;1937 93 25 51 53,1936 92 24 51 51,1935 91 25 47 46,1934 137 71 -48 -49,1933 136
2  202;1;18;1089 56 48 47 -59,1088 111 50 -53 -59,1087 117 52 -53 -62,1086 121 55 -56 -61,
3  202;1;18;1082 119 21 37 40,1081 130 24 34 37
```

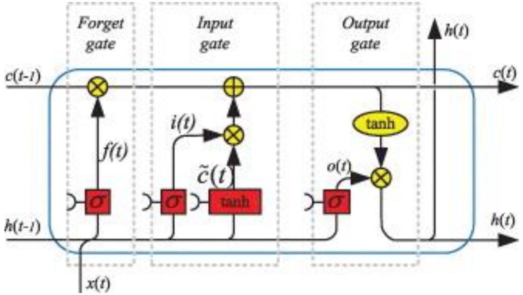
Method: LSTM

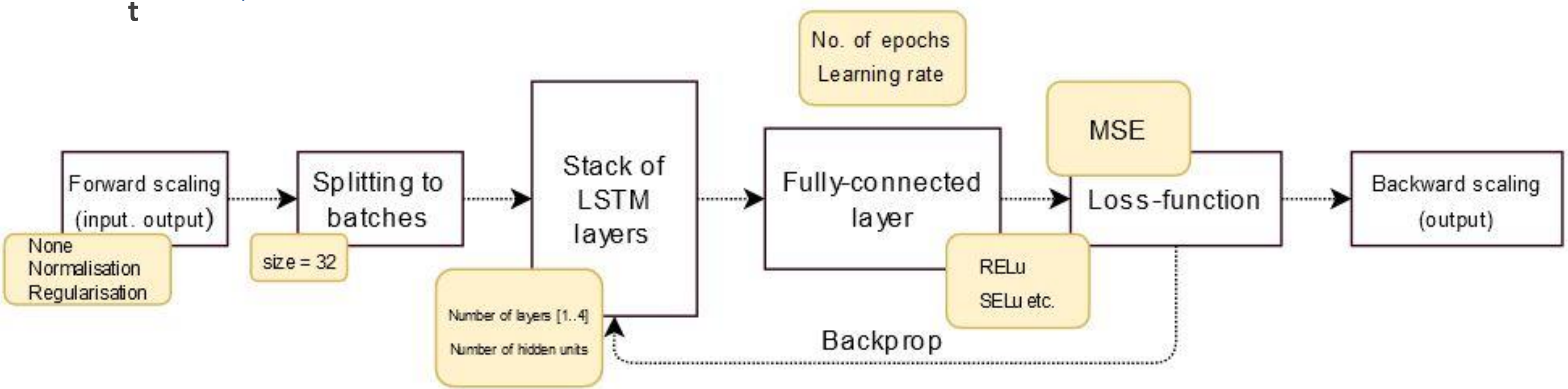
View input as a temporal sequence

Length = 3,5,7,9



LSTM cell





Method: B-spline approximation

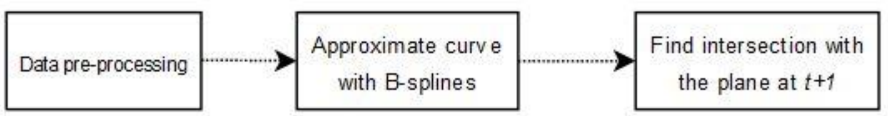
1. Fit a piecewise polynomial curve of degree *n* to a sequence of points in 3D
2. Get get polynomial coefficients. We know analytical expression now
3. Get 3D plane of the next cross-sectional image
4. Find the intersection point(s) of the line and the plane

We will use *n*=2 (line) for simplicity.
Line-plane intersection is unique and easy to find in algebraic form.

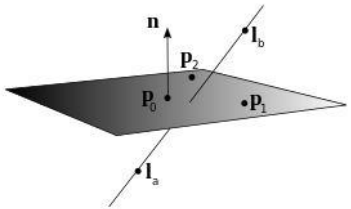
$$d = \frac{(\boldsymbol{p_0} - \boldsymbol{l_0}) \cdot \boldsymbol{n}}{\boldsymbol{l} \cdot \boldsymbol{n}}$$

$$\boldsymbol{l_0} + \boldsymbol{l} \cdot \boldsymbol{d}$$

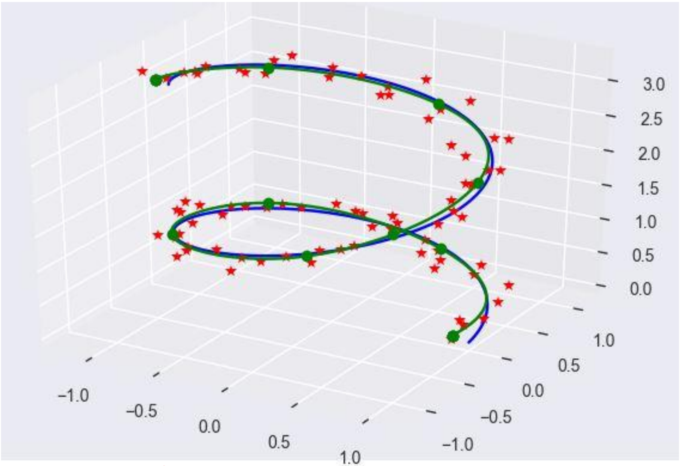
$\boldsymbol{p_0}$ - a point on the plane
$\boldsymbol{l_0}$ - a point on the line
$\boldsymbol{n}$ - a normal vector to the plane
$\boldsymbol{l}$ – a vector in the direction of the line



Line – plane intersection



Example



- Ground truth   * Noisy samples   * Knots   - B-spline approximation

Results: LSTM

Varying input/output scaling

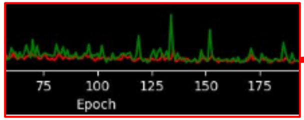
Input Scaling	Output Scaling	Train Loss	Val Loss	Train Loss (last 20)	Val Loss (last 20)	Epochs
None	None	60.73	72.7	76.61	86.59	700
Norm	None	12,57	41,4	15,04	42,37	200
Std	None	3,71	14,76	4,82	17,54	200
None	Norm	47,11	87,03	59,64	81,07	200
None	Std	124,09	385,47	121,14	381,13	200
Norm	**Norm**	**2,66**	**2,69**	**3,46**	**4,32**	**200**
Std	Std	68,49	320,34	69,02	321,06	200
Norm	Std	70,08	322,61	71,33	324,65	200
Std	**Norm**	**2,27**	**3,11**	**2,92**	**3,64**	**200**

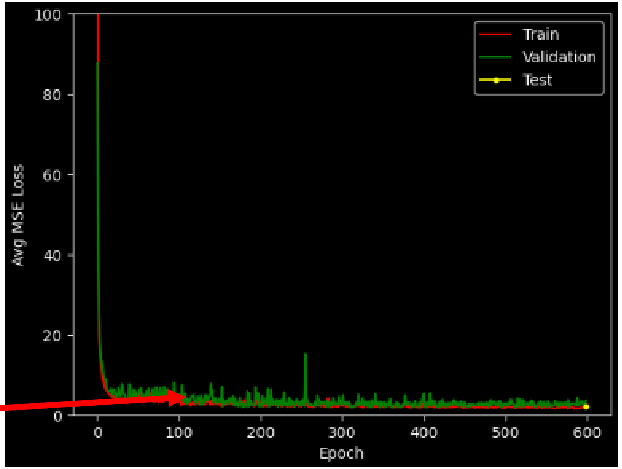
Results with the best parameters

Train Loss	Val Loss	Train Loss (last 20)	Val Loss (last 20)	Test Loss
1.69	3.49	1.65	2.78	2.22

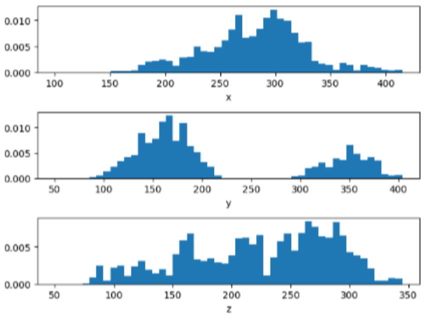
Optimal parameters:

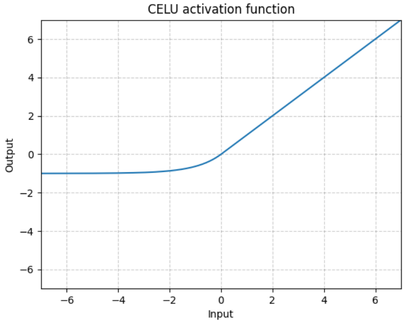
1. Number of LSTM layers = 1
2. Number of hidden units in LSTM = 32
3. Activation function CELU
4. Sequence length = 9
5. Epochs = 200
6. Learning rate = 0.005





Input histograms





$$\mathrm{CELU}(x) = \max(0, x) + \min(0, \alpha * (\exp(x/\alpha) - 1))$$

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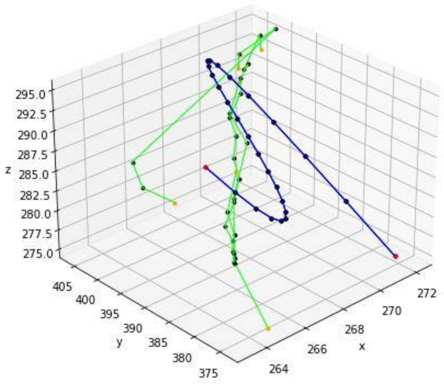
Results: B-spline approximation

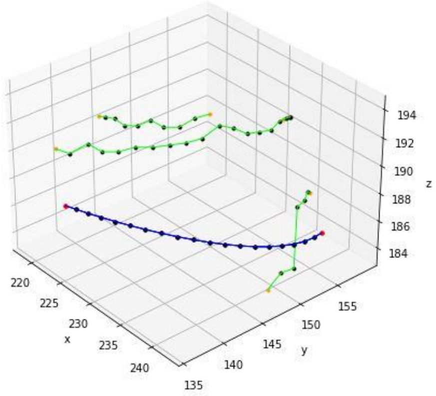
Averaged across 3617 sub-sequences

Sequence Length	MSE Loss
3	0.81
5	0.91
7	1.69
9	2.98

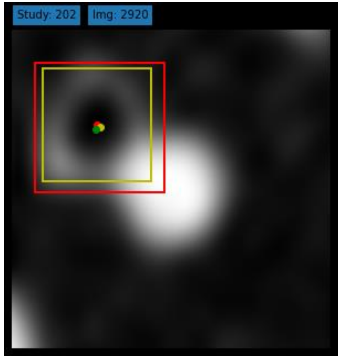
1% of points exceeded MSE 2.2 which is the MSE of the deep learning method

Edges with high MSE

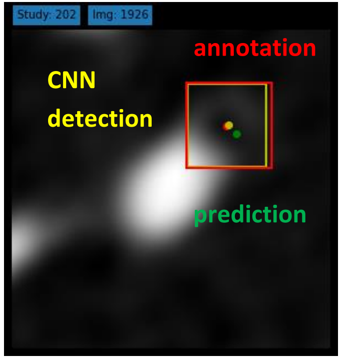




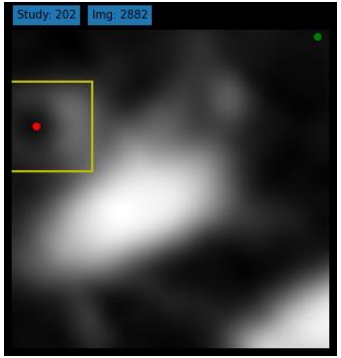
MSE = 0.0402



MSE = 0.2223



MSE = 116.89



Discussion

Deep learning: MSE 2.22

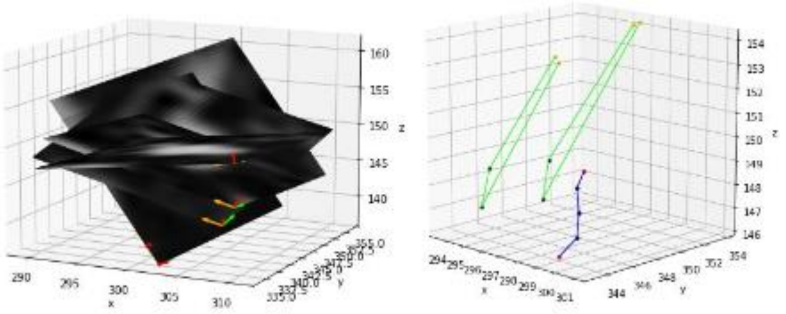
B-spline approximation: MSE 0.81

Deep Learning

- DL require substantial amount of training data – possibly not enough annotated data. Only small number of bronchial branches has been labelled
  Many examples of branches from different special locations are needed.
- Annotation has been preformed by the author, who is not a radiologist. Bias, mistakes.
- Inconsistent sampling. Since the sampled cross-sectional patches may intersect each other at different angles, bronchi spotted at time-stamp t may lie behind the bronchi spotted at time t+1
- Presence of residual bronchi captured in 2D cross-sectional patches, that do not run parallel to the tracked vessel centreline. Additional algorithm has to be implemented to identify and keep only pairing bronchi to the tracked vessel.

Potential benefits of RNN if one can collect enough consistent data:

- Capture a different level of non-linearity at various bronchi generations.
- Automatically learn the direction of branches based on their spatial locations.
- Such model would allow not only more accurate estimate for tracking, but also use of the model for synthetic data generation



The vessel trajectory is nearly linear, and the bronchi trajectories are almost U-shaped

Discussion

- Sampling mechanism of cross-sectional images from the baseline method has to be improved to create consistent samples.
- Alternatively, the inconsistent samples have to be removed manually or automatically, but that might be a grand challenge to do.

B-spline approximation

- The spline method showed robust and accurate results where the geometry of branches is approximately linear since we used linear splines for simplicity.
- To overcome the issue with inconsistent sampling, we find an intersection of the fitted spline with the plane of the next cross-sectional image.
- The method can be improved by using quadratic or cubical splines; however, finding multiple intersections with a plane in 3D might not be a simple task to do.
- The downside of the method is the pre-defined assumption of curves' shapes, i.e. linear, quadratic etc. without the ability to generalize.

Recommendations for improvements and future research

- The process of generating new labelled data based on the outputs of the trained standalone CNN involves the only one trained person and observation of images without context. It would be beneficial to look at each image and its neighbors from the same edge as well have a better-designed protocol.
- Process the data in a hierarchical manner as opposed to a random draw of individual cross-sections or branches. This way, we could benefit from the inclusion of contextual and structural information. Algorithms based on convolutional LSTM or graph neural networks would be a good choice.
- Sampling in 3D (cubes or spheres) as opposed to 2D.
- Focus on bifurcation points. The challenge is that cross-sectional images of bronchi at bifurcation look different from a ring-shaped single bronchus.

Thank you!