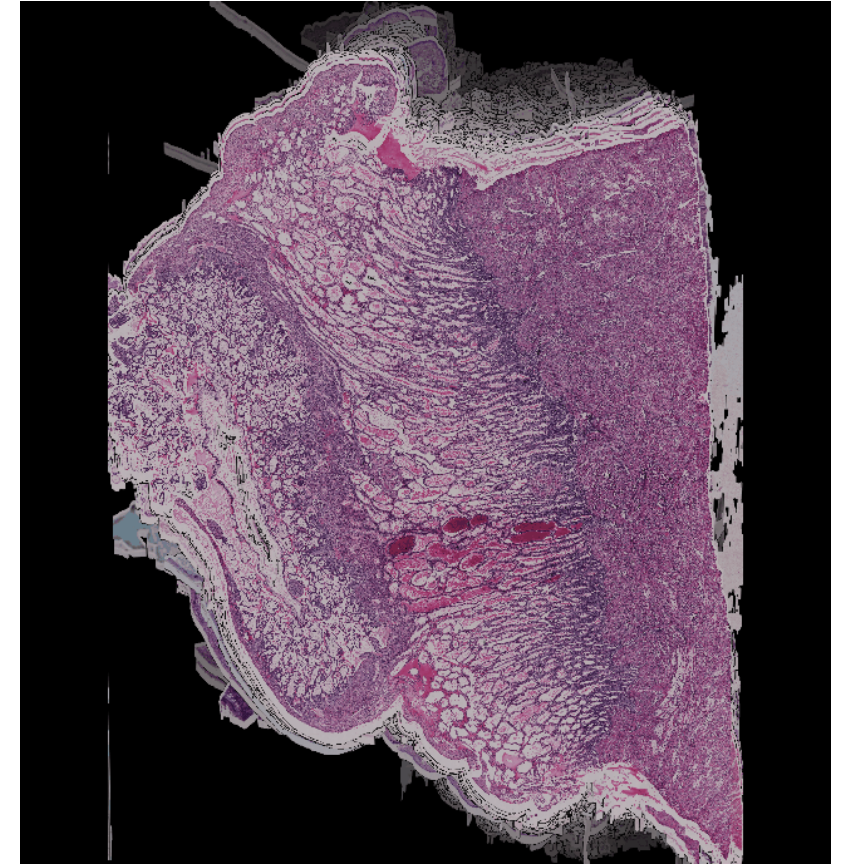


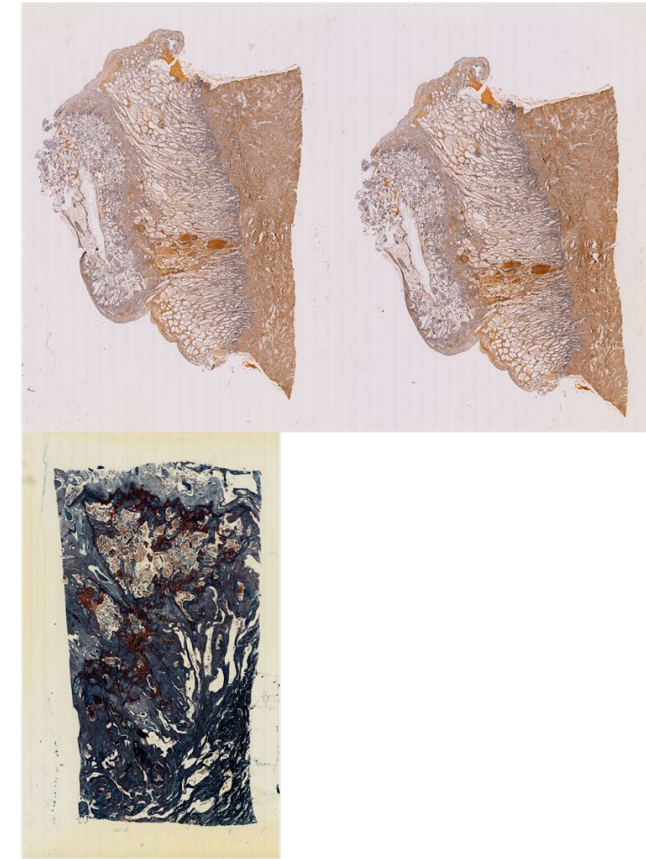
# Creating a 3D Virtual Atlas of the Uterus

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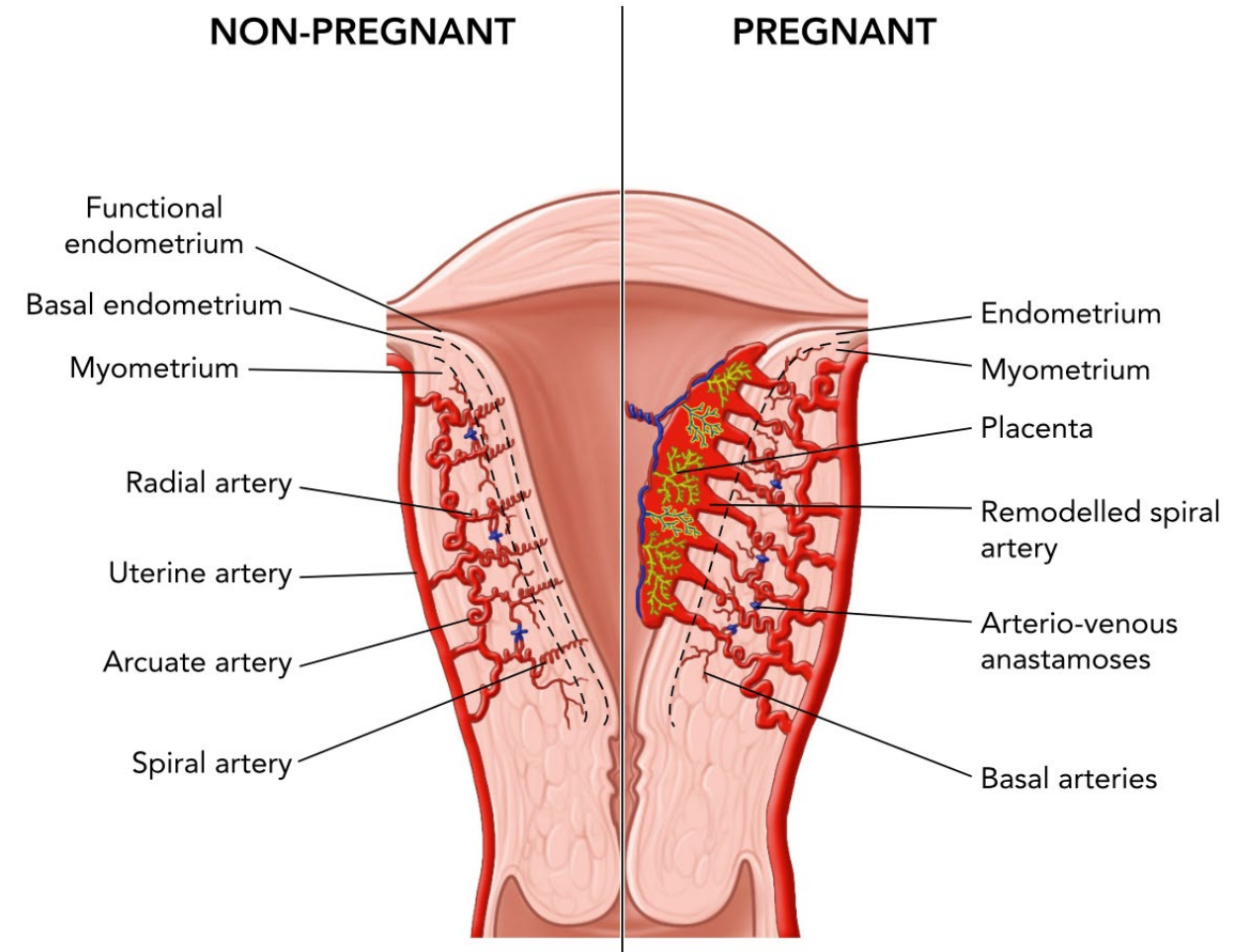
## Overview of project

- Masters project with the Placenta Modelling Group at the Auckland Bioengineering Institute
- Historical data set of uterine samples at varying gestations have been digitised
- Project outcomes:
  - Samples have been recreated into 3D reconstruction
  - Segmentation of key tissue types



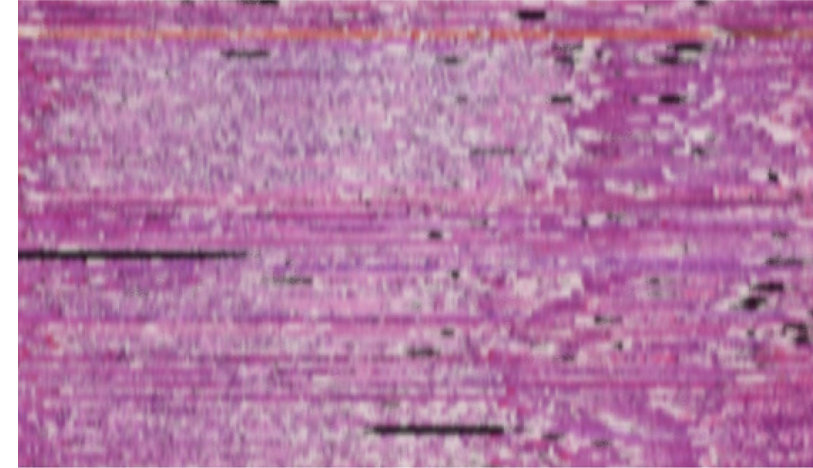
## Why is this work important?

- One of the least understood organs in the human body
  - Mostly qualitative
  - Animal models or low resolution non-invasive imagery insufficient
- Fetal conditions are not well understood
  - e.g. Fetal Growth Restriction (FGR) is poorly diagnosed during pregnancy
- Visualisation is key to quantitatively describing the uterine vasculature

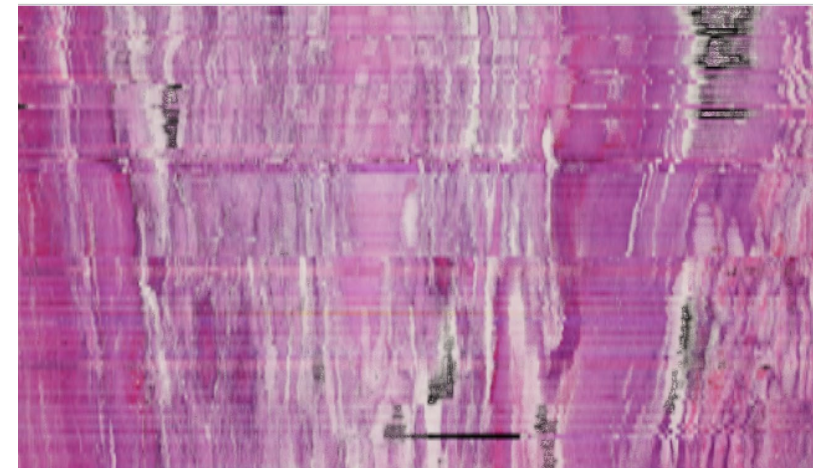


# Registration

- Features exhibit large linear and nonlinear deformations
  - Linear registration minimises translation and rotation errors
  - Non-linear registration is the abstract correction of visual continuity
- Key to alignment is how you measure sample deformations



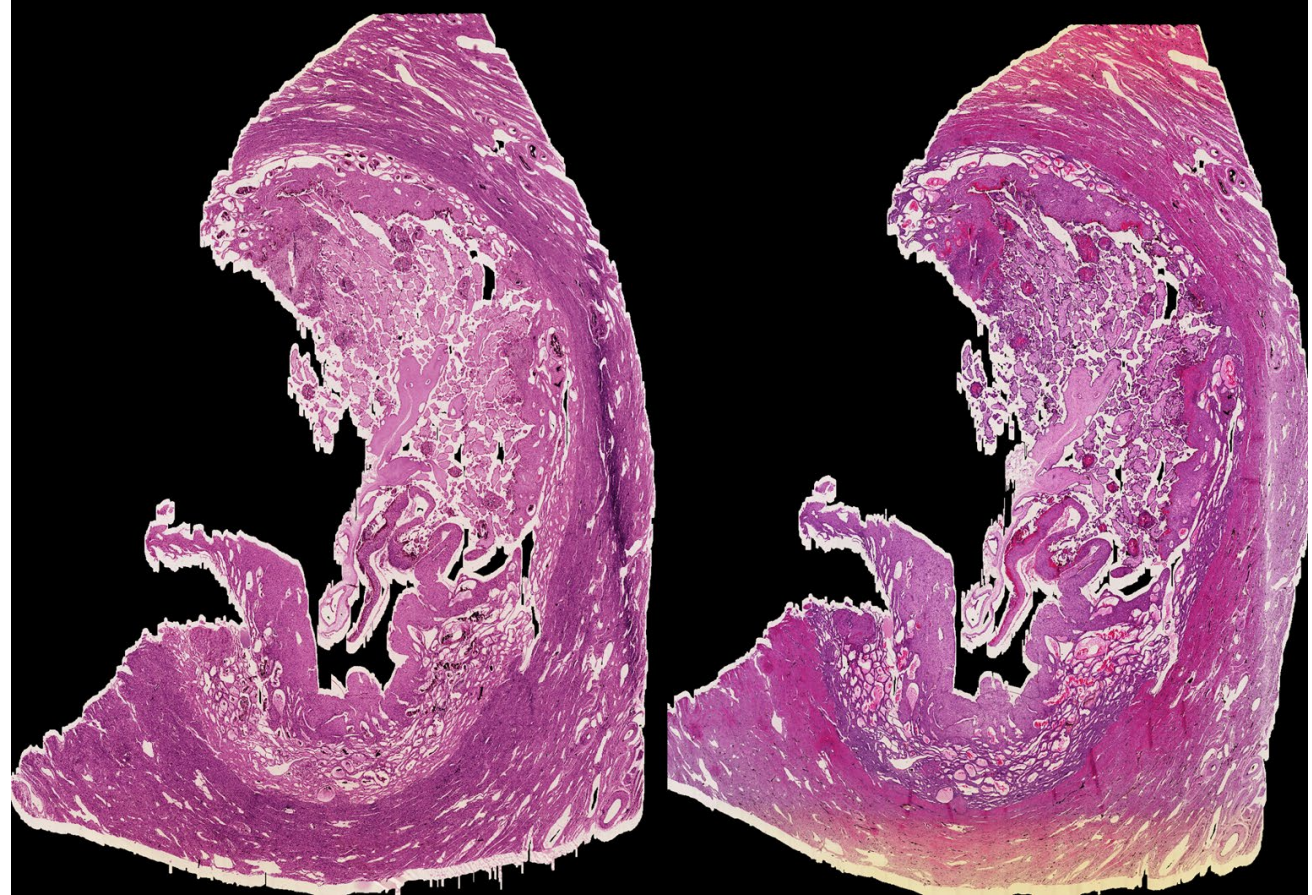
Unregistered specimen



Registered specimen

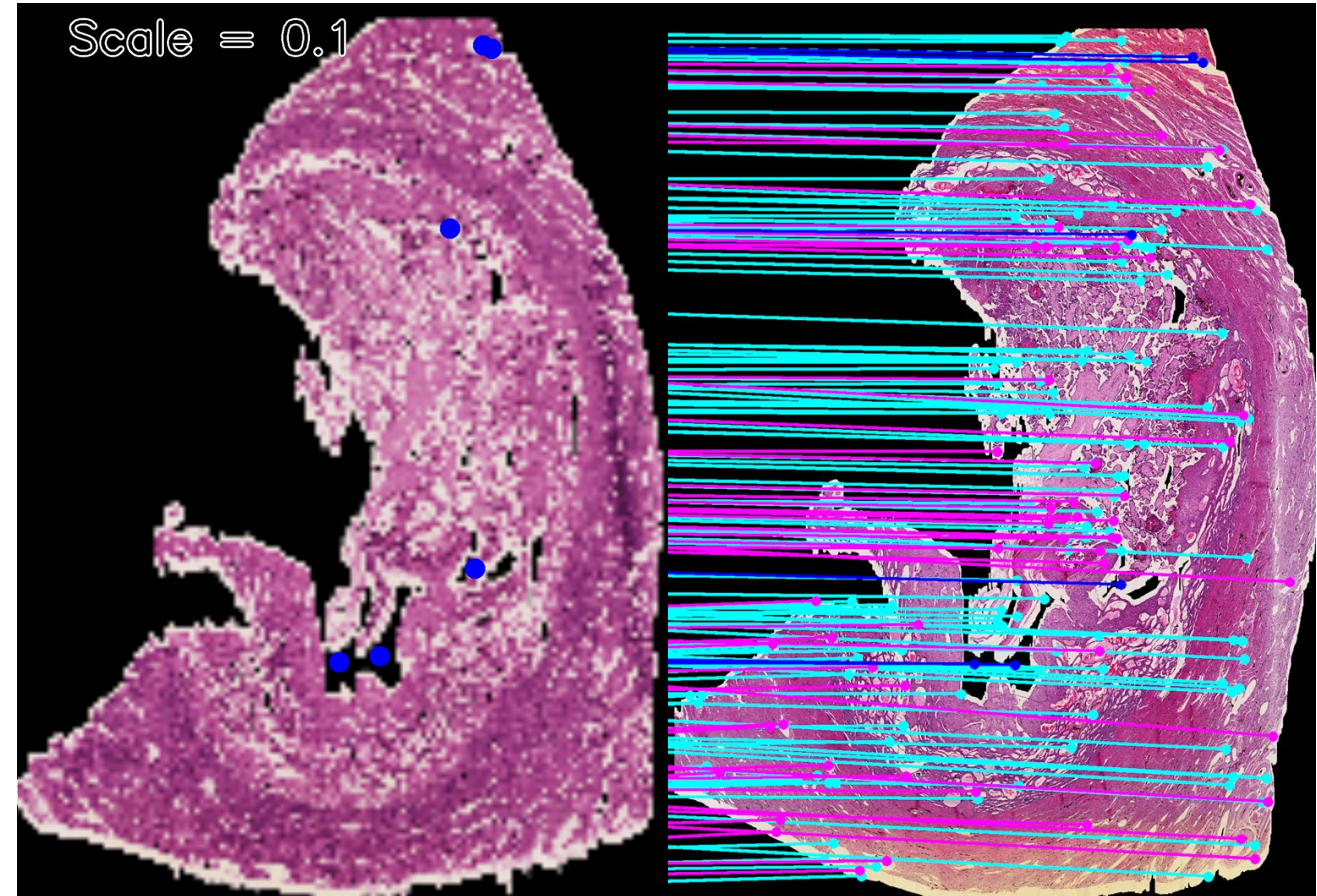
## Linear Registration, Feature finding

- Features represent the most robust method for identifying the relative positions of the samples
- Feature finding performed by SIFT in particular to rotation invariance []
- Naive SIFT is not useful or intuitive
- “Spatial cohesiveness” is finding features which are biologically relevant



## Linear Registration, Feature finding

- Manual feature identification is considered “gold standard”, however very slow and high variability
- Codified the process of manually finding features: find prominent feature first and use those to find other features
- Multi-resolution feature search using low res/high strength features to initiate feature searching

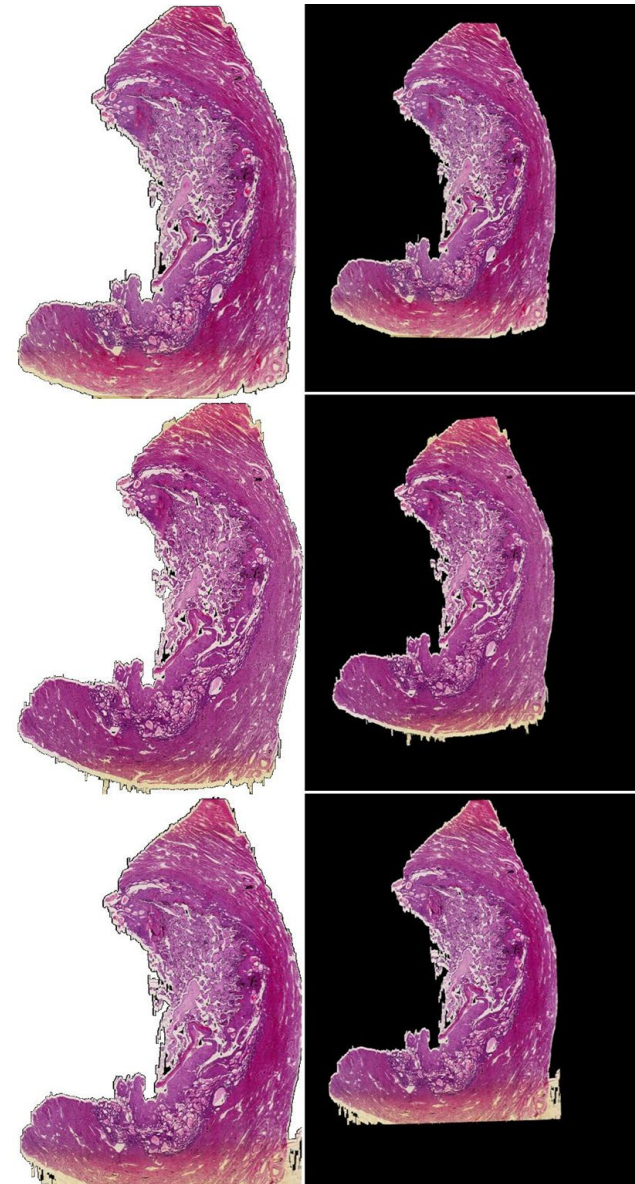


# Linear Registration

- Linear registration minimises rotation and translation of the **features**
- Performed using `scipy.optimize.minimize`
- If not below threshold, features of highest error removed and repeated

while True:

```
featureTran = translate(features)
featureMod = rotate(featureTran)
err = errorPerFeature(featureMod)
if err < threshold:
    break
else:
    features =
```



## 0th image, Reference image

Translation (pixels moved from top left) = (0, 0)  
Rotation (angle anti-clockwise, centre of rotation) = 0°, (0, 0)

## 1st image, aligned to 0th image

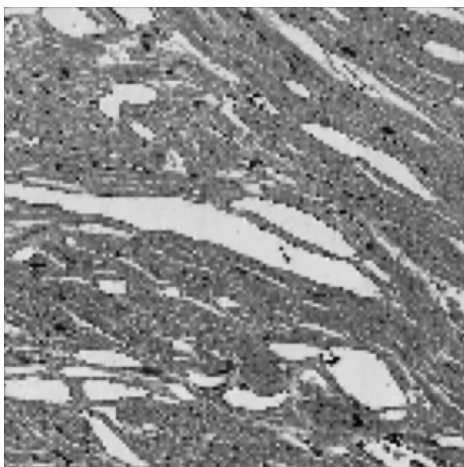
Translation = (127, 1)  
Rotation = 5.4°, (672, 1022)

## 2nd image, aligned to 1st image AFTER translation

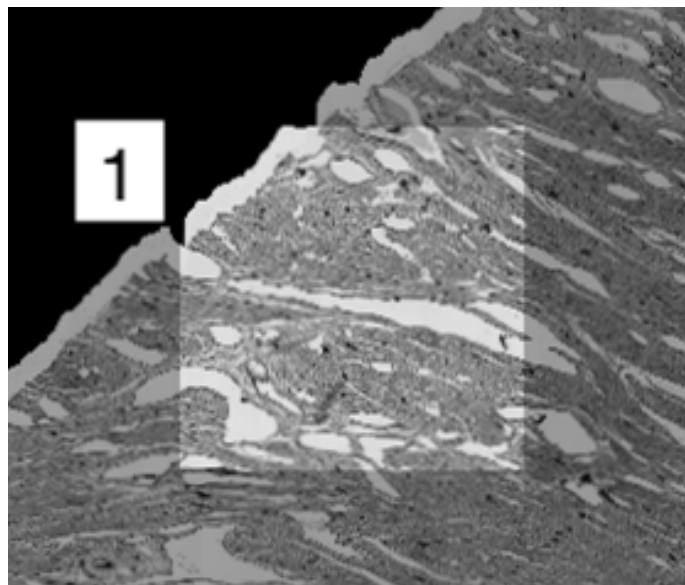
Translation = (135, 87)  
Rotation = 1.7°, (703, 825)

## NL Registration, Feature tracking

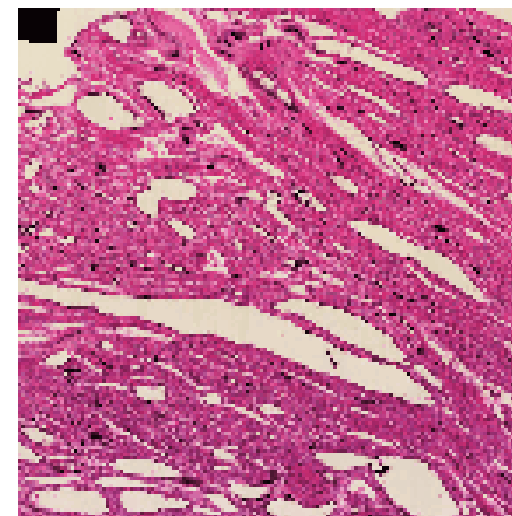
- Finding spatially cohesive features as well as visually similar features
- Uses Phase Cross-Correlation to minimise the visual differences



Reference section



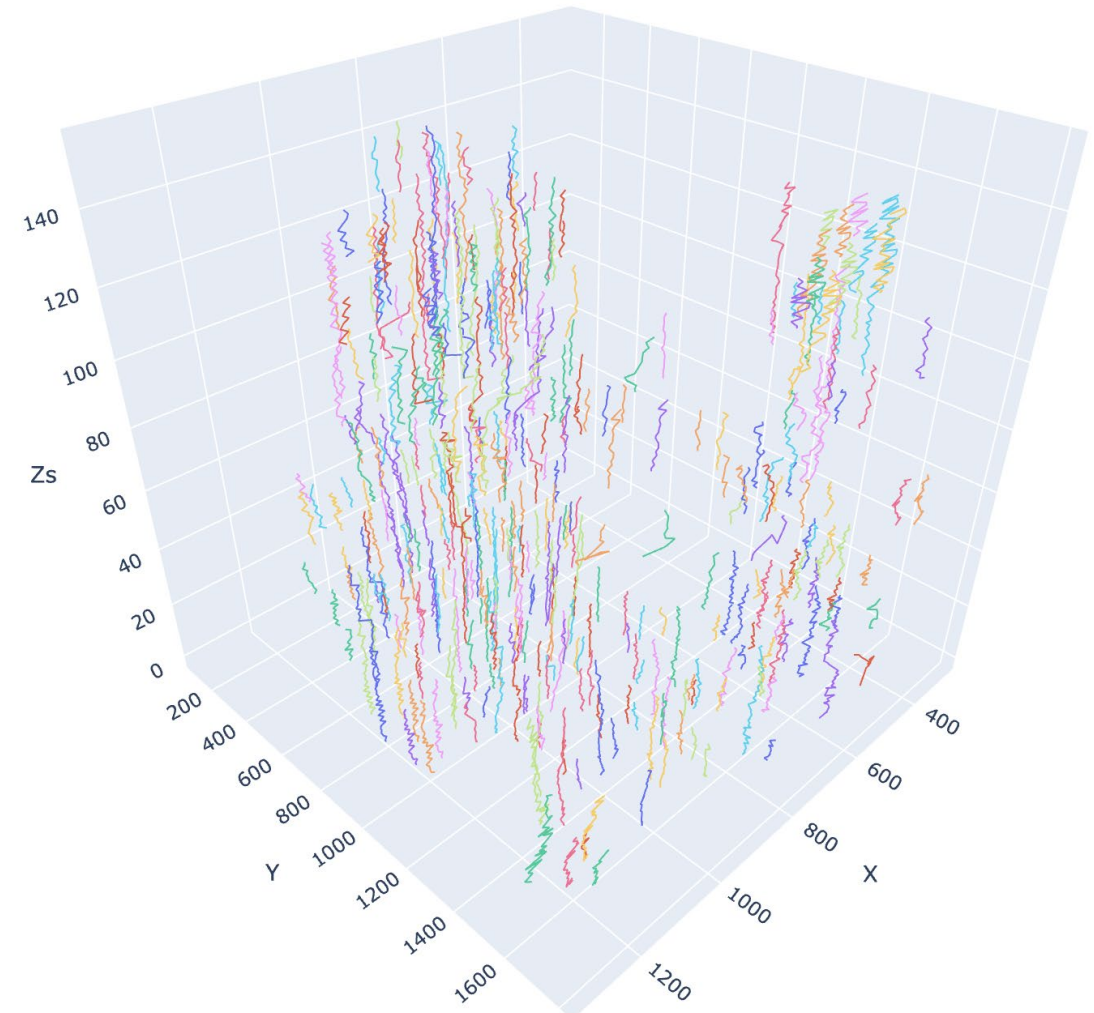
Target section search



Final feature through  
specimen

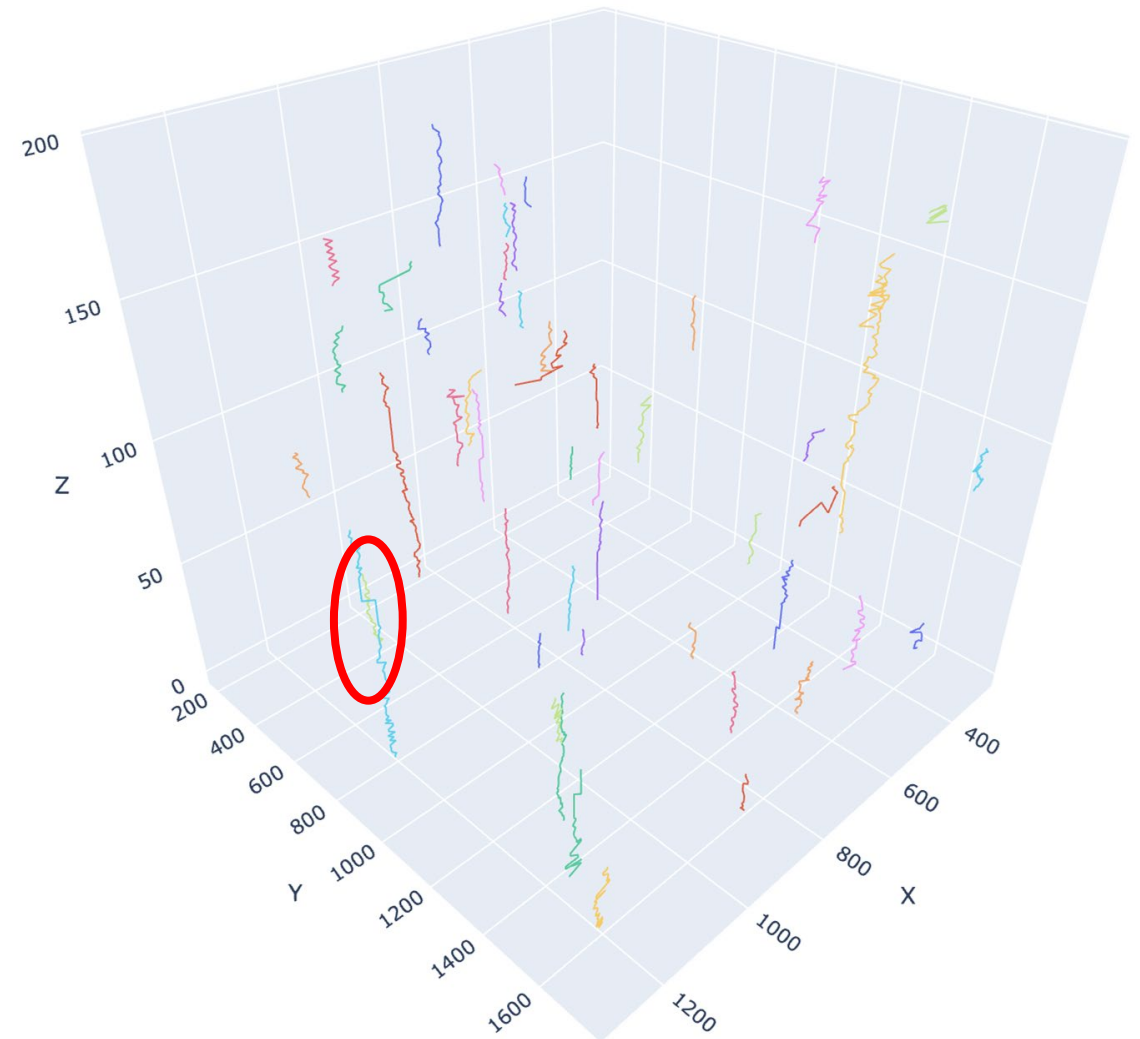
## NL Registration, Feature tracking

- The features are tracked through the entire specimen
- Spatial cohesion is checked at each sample
- Feature stops when no longer spatially cohesive



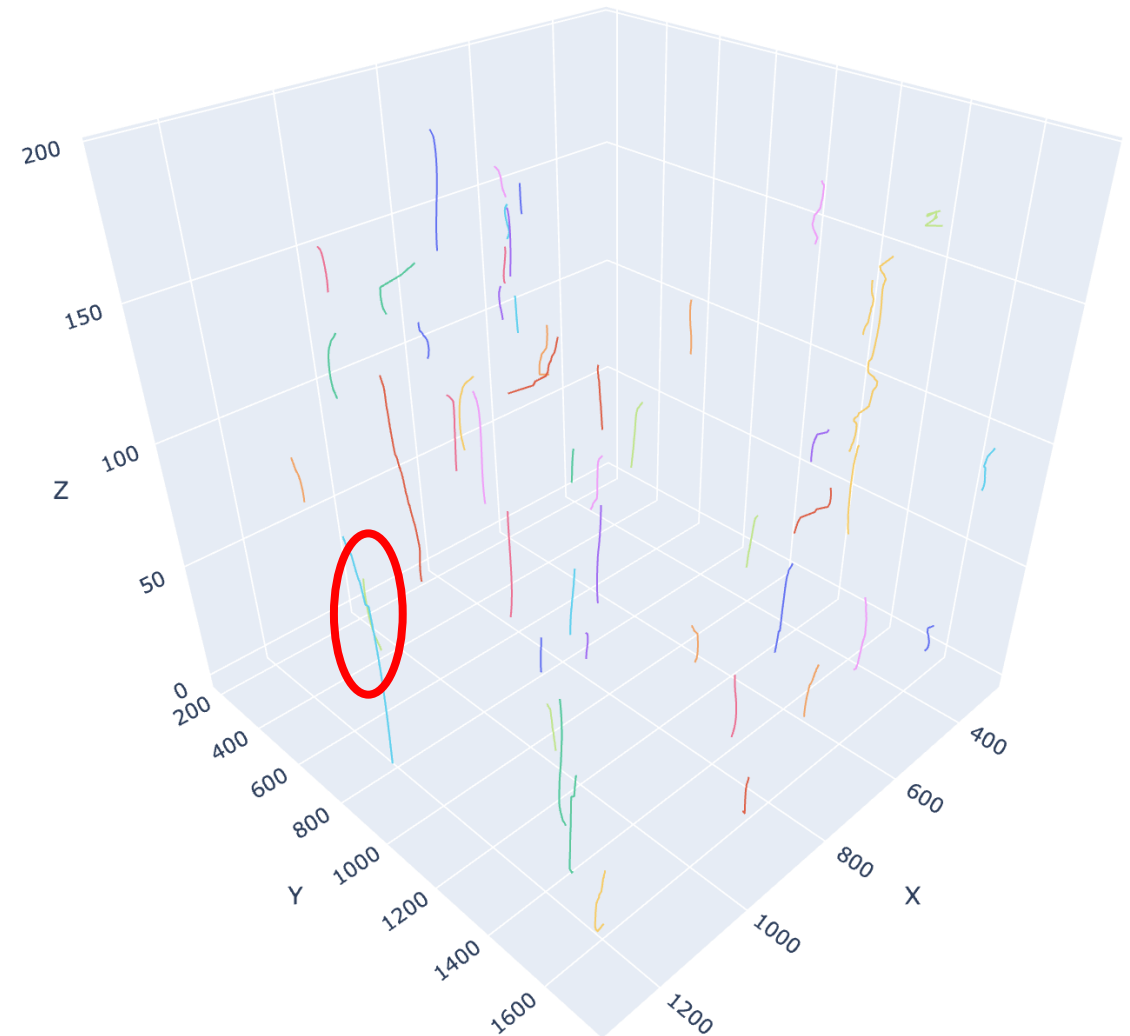
## NL Registration, Feature selection

- Features are selected to ensure spread of features is sufficient for non-linear deformations (next step)
- Feature selection is determined by:
  - Ensuring there is space between the possible features
  - Prioritising either their length or smoothness
- Missing samples are interpolated between features



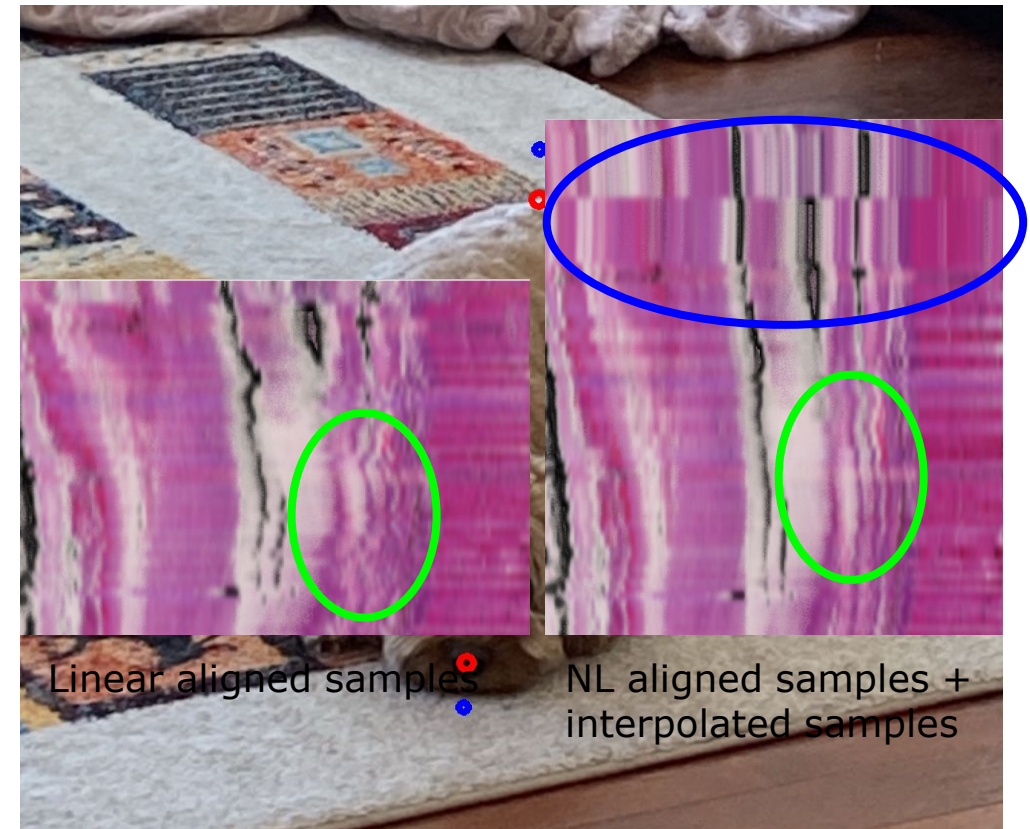
## NL Registration, Feature smoothing

- Features in tissue progress smoothly (analogue)
- Features in digitised samples are discrete and sometimes non-continuous due to deformations
- Trajectory of samples is smoothed by a 3D cubic B-spline



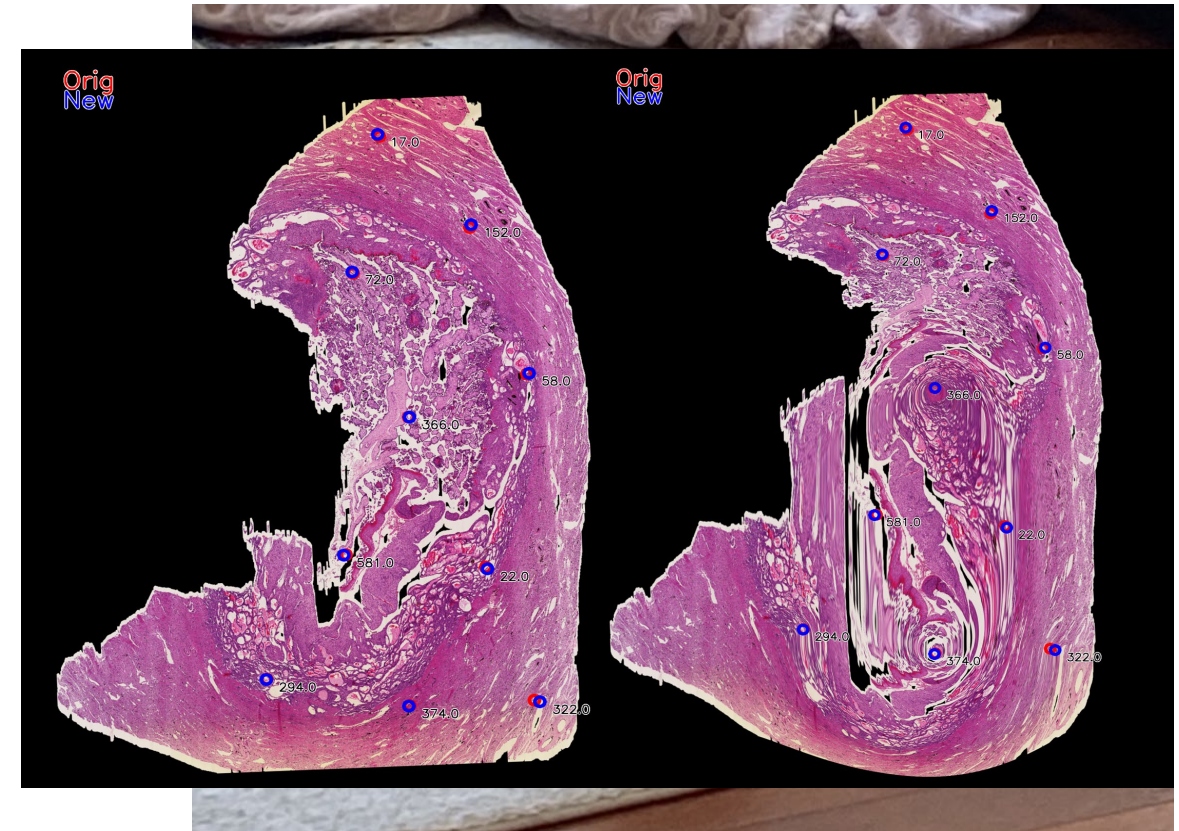
## NL Registration, success

- Tissue with the smoothed feature trajectories, we can compensate for non-linear deformations
- Helps to create more biologically realistic visualisation
- Implemented by `tensorflow_addons.image.sparse_image_warp`

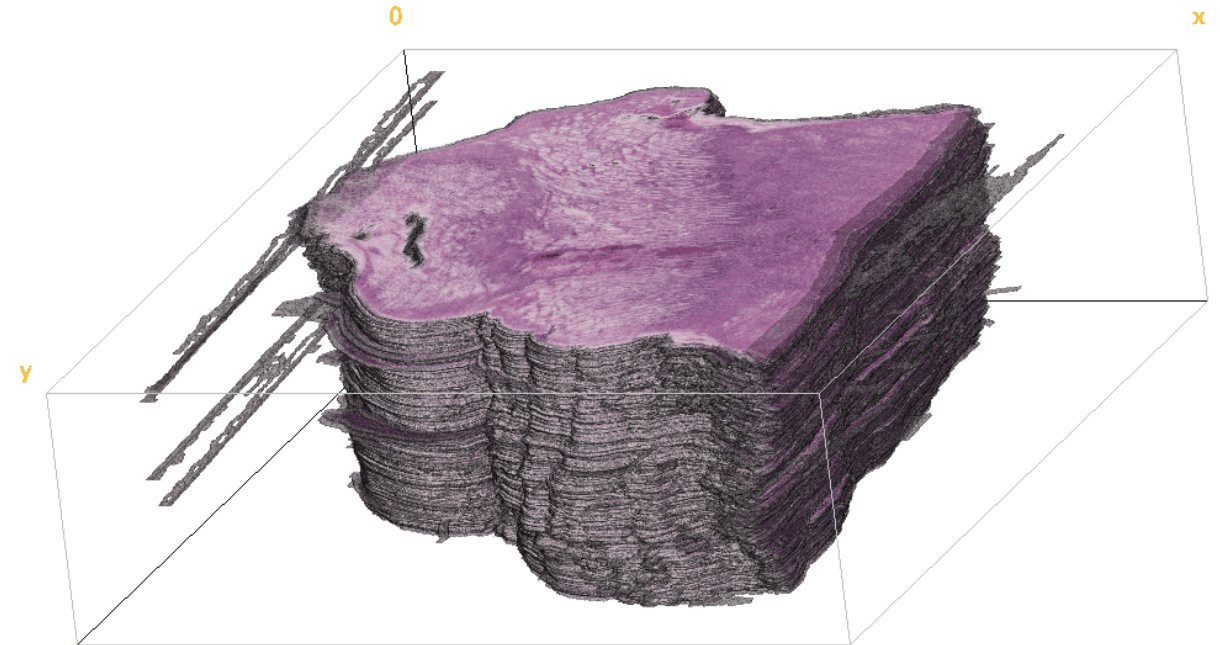
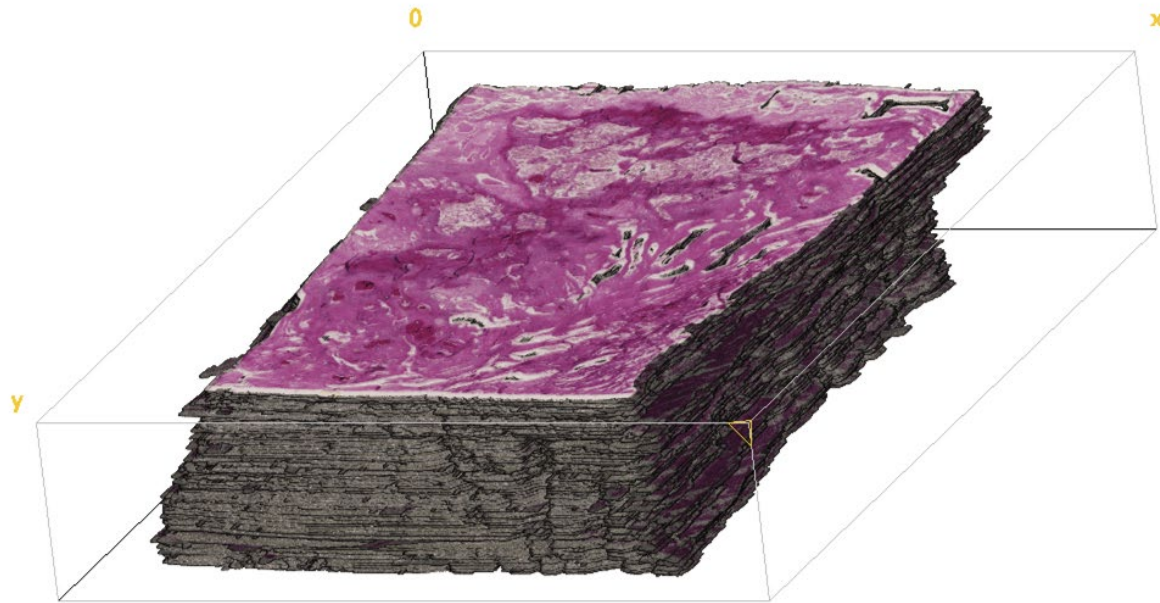


## NL Registration, unsuccessful

- Works well for small deformations which are well-spaced apart
- Feature selection reduces the occurrence of “impossible” deformations
- Causes may be:
  - Incorrect feature tracking
  - Smoothing creates impossible situations
  - Interpolations are not constrained properly



# Full registration

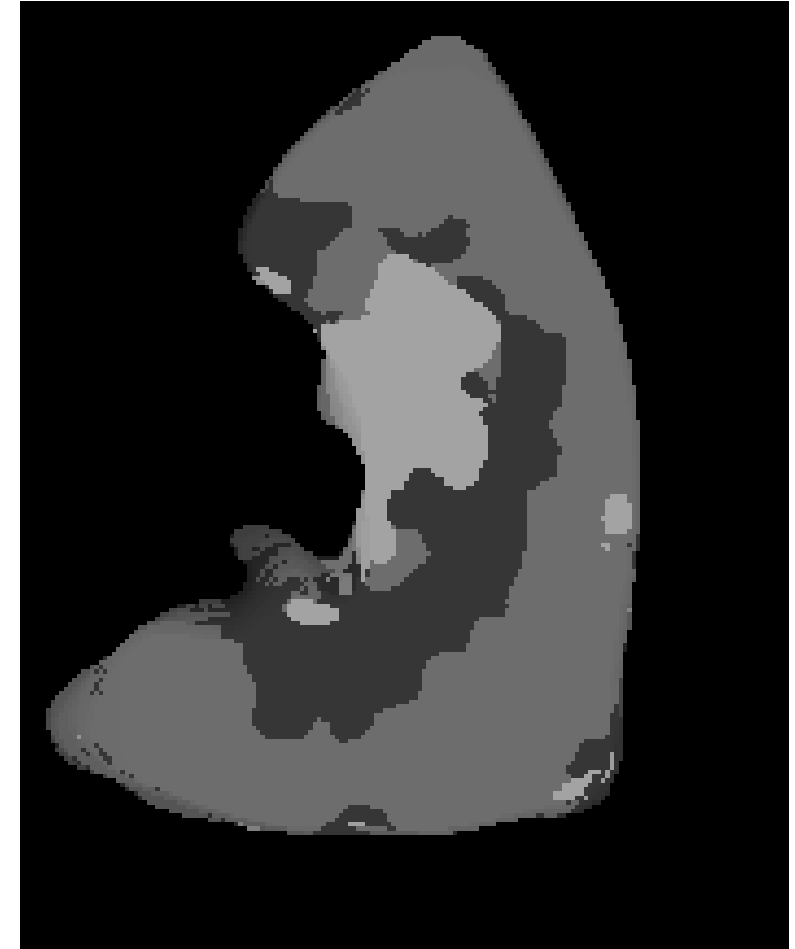


## Segmentation

- Training data created by the tracked features already made

### **two for the price of one**

- Key tissue types: myometrium, decidua and villous tree
- Model created with imagenet pre-trained, Resnet101 network
- Similar results between models



## Future work

- Segmentations with 3D convolutions
  - More accurate tissue type segmentation
  - Segment out the smaller structures
- Improved nonlinear deformations

## Acknowledgements

- Alys, Jo, & Hanna
- Graham Burton, Centre for Trophoblast Research

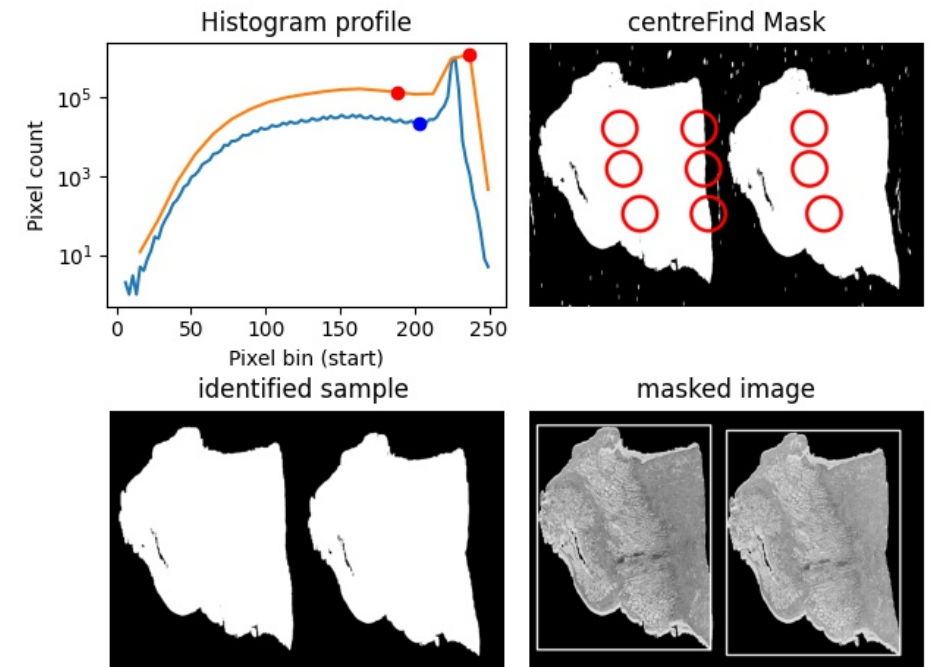
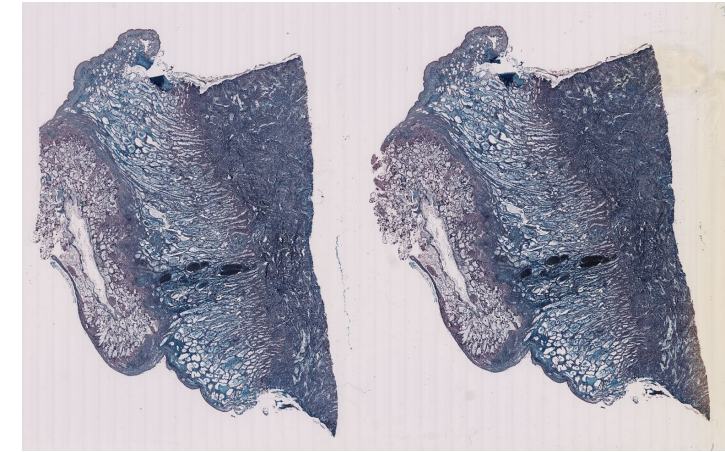


**Thank you for listening**

**Any questions?**

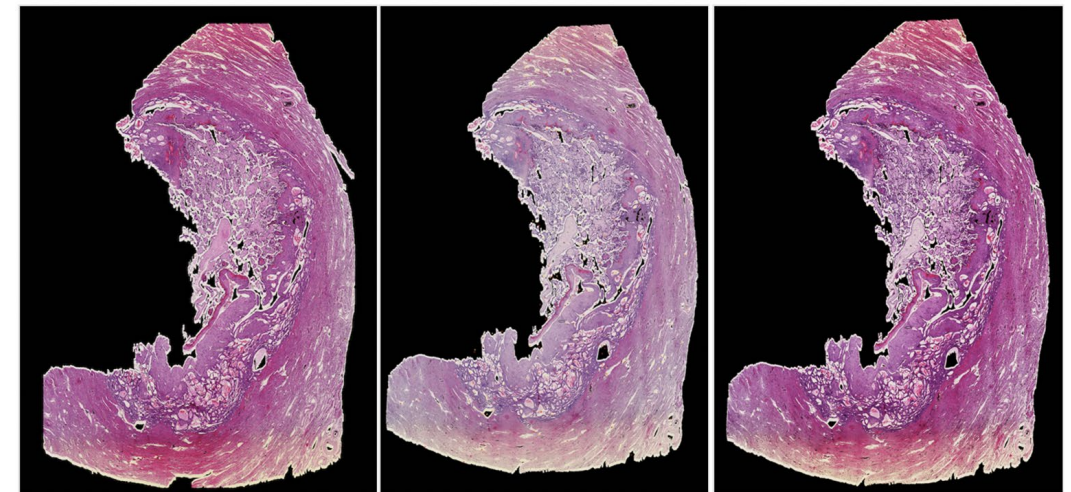
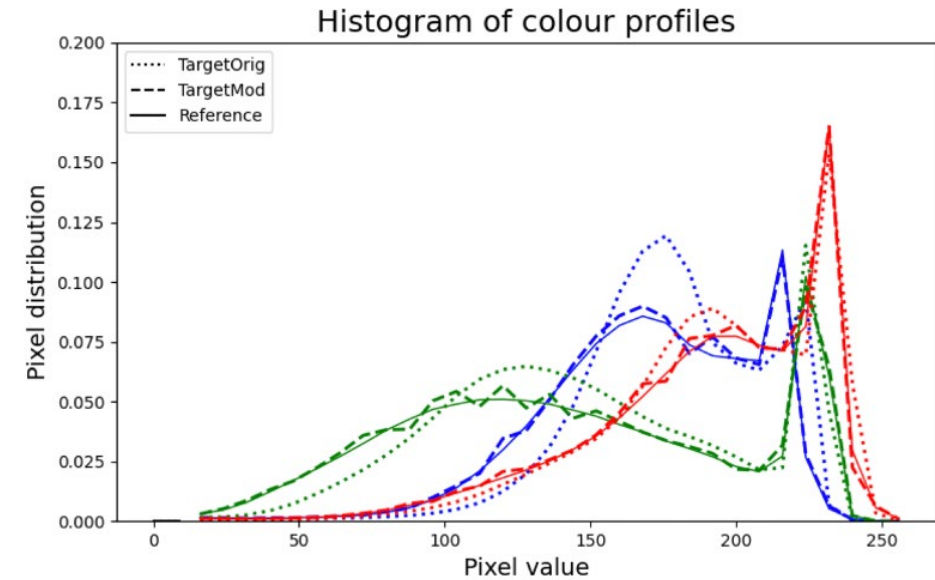
## Specimen Extraction

- Samples are presented in their tissue blocks, often with multiple samples per block
- Isolating samples critical for further processing
  - a. Differentiate background from foreground
  - b. Identify individual sample positions
  - c. Extract individual samples
  - d. Normalise colours



## Colour correction

- Stains represent different cell structures
- Multiple stains used, hard to visualise and process stacked samples
- Normalise the colour distributions of each channel relative to a reference sample
- This method creates visual consistency



Reference image   Target Original   Target Modified