Identification of paediatric tuberculosis from airway shape features

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Introduction

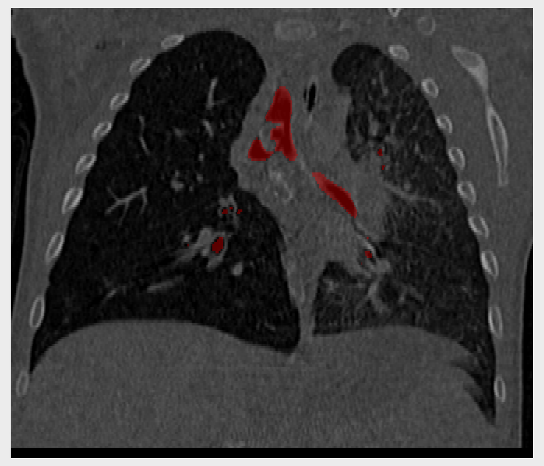
- Prevalence of TB is still high, particularly in developing countries
- Poor detection rates in children
- Primary TB in children is characterised by lymphadenopathy
  - leading to displacement and stenosis of airway branches

Aim:
- Assist in the detection of TB from airway shape
- Segment and model airway shape changes from CT scans

Method

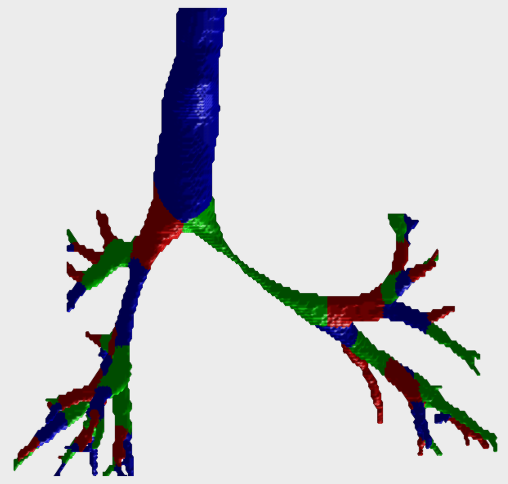
Airway Segmentation

- Detect trachea
- 3D morphological closing and reconstruction
- Seeded region growing



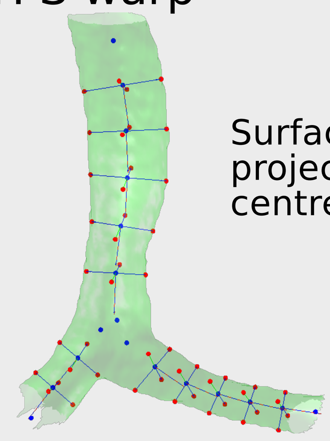
Skeletonisation and branch point detection

- Iterative topology preserving thinning
- Branch point detection by voxel connectivity



Airway Correspondence

- Equidistant sampling of centreline
- Projection of points onto surface orthogonal to centreline
- Surface points used as landmark points for TPS warp



Thin plate spline warp

- Warp vertices onto a template airway to generate matching vertices
- Landmark points direct warp by minimisation of bending energy
- ~1500 vertices

$$\boxed{f_j(P_j)} = \sum_{i=1}^{k} \boxed{w_{ij}} U(P_j - P_{ij}) + a_0 + a_x x + a_y y + a_z z$$

Landmark points match exactly. Other points interpolate landmark points

Weighting factors found from landmark points on template and airway

Local Alignment

- Local alignment of surface required after TPS
- Forcing function directs alignment
- Expansion/contraction force improves matching with stenosed branches

$$F_{i,1} = \vec{r}_i - \vec{t}_i$$

Closest point

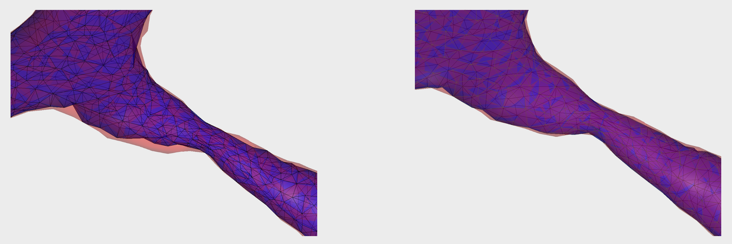
$$F_{i,2} = \sum_{j}^{p} \hat{v}_j(||\vec{v}_j|| - ||\vec{v}_{0j}||) \quad \text{where } \vec{v}_j = \vec{t}_j - \vec{t}_i$$

Mesh preserving term

$$F_{i,3} = \hat{n}_i(\hat{n}_i \cdot F_{i,1})$$

Expansion/contraction force

$$F_{i,tot} = \alpha F_{i,1} + \beta F_{i,2} + \gamma F_{i,3}$$



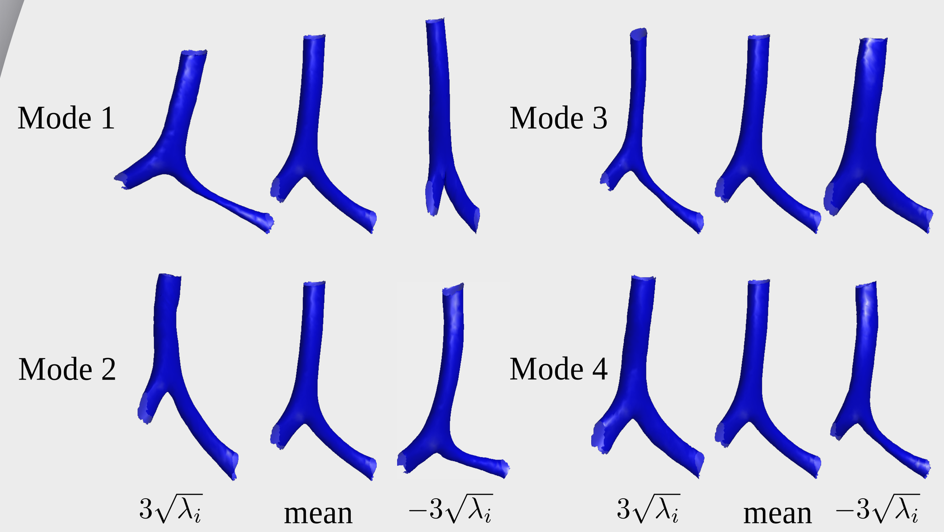
Closest point matching (F1+F2)

Improvement using expansion/contraction force (F1+F2+F3)

Method 1: PCA Features

- 3n input vector where n is the number of vertices
- Projection onto orthogonal components to generate features

Airway variation along the first 4 modes



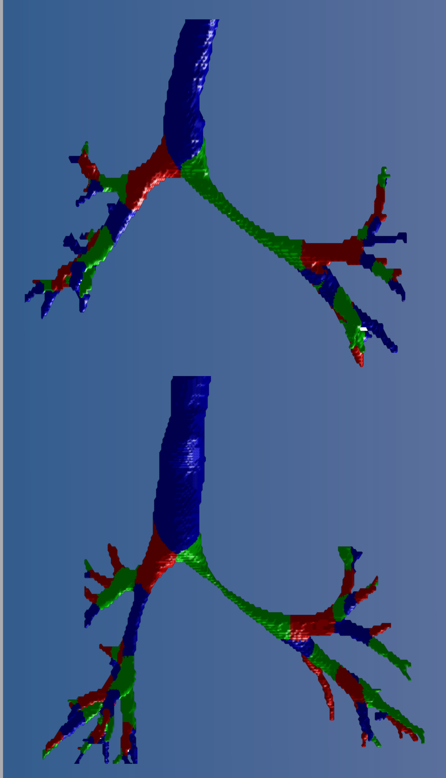
Method 2: Branch Features

Alternative set of features:
- ratio of orthogonal diameters
- ratio of local minima and maxima
- branch length and diameter
- carinal angle

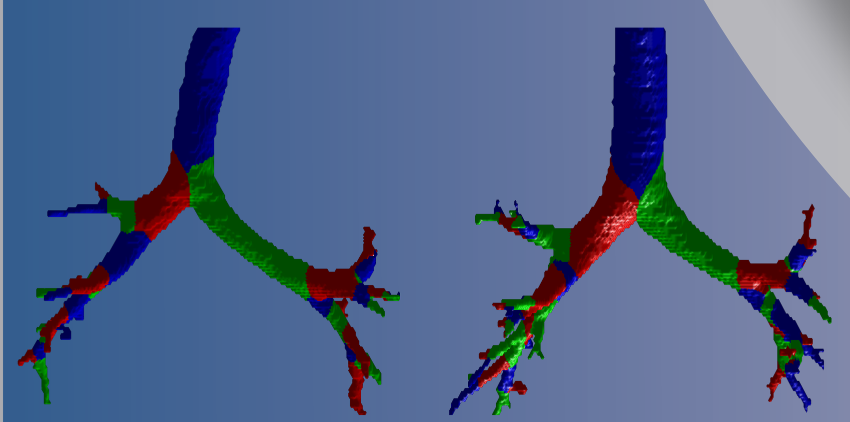
Dataset

- 61 Patients
  - TB and non-TB
  - Mean 33 months
  - Min 2 months
- CT Scan
  - Axial plane 0.3-0.5mm
  - Slice thickness 0.7-1mm

Airways of TB patients with narrowing in left main bronchus and bronchus intermedius:



Airways of non-TB patients:



Classification

- Classification to compare two feature vectors:
  - 10 PCA modes
    - 90% of airway variation
  - 10 radius based features
- Support vector machines
- Parameter selection and validation using nested leave-one-out cross validation

Results

- Detection of paediatric TB cases from airway shape

	Sensitivity	Specificity
PCA feat	86%	91%
Branch feat	86%	94%

Conclusions

- Both PCA based features and branch features accurately distinguish between TB and non-TB cases
- This method shows the potential of airway shape analysis to assist in the detection of airway pathology
- Future work:
  - Test method on a larger dataset
  - Local analysis of pathology

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