RIB DETECTION IN MRI USING STATISTICAL SHAPE AND MR APPEARANCE MODELS

Golnoosh Samei, Gabor Szekely, Christine Tanner

Computer Vision Lab, ETH, Zürich, SWITZERLAND.

Background: Magnetic resonance guided high intensity focused ultrasound (MRgHIFU) therapy is a promising new technology to ablate tissues non-invasively. Exact knowledge of the location of the target organ as well as the risk structures on the beam path is crucial to a successful therapy. One particularly important structure is the ribcage due to its vicinity to the liver, and bones’ absorption and reflection of ultrasound energy causing harm to themselves and the surrounding tissues. Therefore, it is necessary to detect ribs in MR images.

Aims: We tackled the problem of rib detection in MRI. This is a challenging task, as bones do not emit sufficient magnetic signal and are relatively small structures.

Methods: We used two independent datasets from healthy volunteers. A CT dataset including 20 end-inhale images and an MR dataset of 21 end-exhale MR images with spatial resolution of \(1.37 \times 1.37 \times 1.37\, \text{mm}^3\), and \(1.33 \times 5 \times 1.33\, \text{mm}^3\), in anterior-posterior, left-right, and inferior-superior directions, respectively.

Our method is based on combining a ribcage geometric model generated from CT images and a rib appearance model from MRIs. It requires the definition of one landmark per rib, and 2 extra landmarks per subject. For the ribcage geometric model, ribs were segmented in CT images using a region growing algorithm. Correspondence between ribs was established by dividing each rib into two segments at its angle point (most posterior point) and uniformly subdividing each segment by a fixed number of points (100 in total). The geometry of each rib was initially defined by its shape (3D locations of 100 points), length and orientation (3 angles). Since these attributes have a high degree of correlation in a ribcage, we built statistical population models based on principle component analysis (PCA) to find their main modes of variation for ribs 7-10, which enclose the liver. First the shape parameters were reduced to 2 principle components (covering 96% shape variability) per rib. Then further PCAs were performed for \(8 = 4 \times 2\) rib shape parameters (2 PCs), \(12 = 4 \times 3\) Euler angle values (5 PCs), and 4 length values (2 PCs), keeping enough PCs to cover 95% variability.

The appearance model was based on 4 region-specific random forest classifiers [1], which were trained to discriminate between rib and non-rib patches, see Fig. 1. The classifiers employed normalized intensity based features.

The aforementioned 9 PCA coefficients, (2 for shape, 2 for length, 5 for angle), were used to generate rib centerline hypotheses, consisting of 4 centerlines, each having 100 points. The hypotheses were generated by uniformly drawing samples from the interior of a 9-D hyper-ellipsoid, which covers 95% of the multidimensional Gaussian distribution associated with the PCA models. Finally, the most likely rib location was determined by accepting the hypothesis whose corresponding image patches provided the highest probability of rib appearance.

Results: The RF classification accuracy was 89% on average. The extracted centerlines from 21 volunteers had a mean (90%) distance of 8.1mm (17.96mm) from the manually selected centerlines.

Conclusions: We have shown that, despite their poor visibility, ribs can be detected in MRI by taking advantage of the accuracy of CT images in observing the ribs. This was achieved by learning a statistical ribcage shape model from CT and combining it with an MR appearance model.

Acknowledgements: We acknowledge funding from the European Union’s 7th Framework Program (FP7/2007-2013) under grant agreement n° 270186 (FUSIMO).


Figures: (a) The predicted centerlines (green) and the manually selected points (red) on a sagittal slice. (b) The probability heat map of the same slice. (c-e) The predicted centerlines (red) overlaid with the manually extracted ground truth (blue).