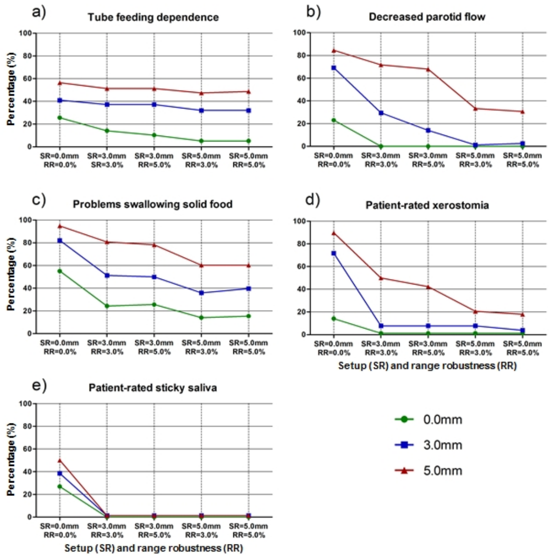

Figure 1: Percentage of patients selected for IMPT as a function of margins and robustness settings for each of the five NTCP models. A ΔNTCP-threshold of 10% for the grade II models (b-e) and 5% for the grade III model (a) was used. a) Wopken et al., b) Dijkema et al, c) Christianen et al., d) and e) Beetz et al.

Conclusion

This study shows that treatment accuracy cannot be ignored in estimating the number of patients that will be selected for proton therapy based on comparative treatment planning and NTCP evaluation. We also conclude that IMRT as well as IMPT should be optimized for accuracy to ensure a sustainable use of proton therapy.

Proffered Papers: Imaging and image analysis

OC-0155 Automated lung tumour delineation in cine MR images for image guided radiotherapy with an MR-Linac

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Purpose or Objective

Respiratory-induced lung tumour movement is a significant challenge for precise dose delivery during radiotherapy. MR-Linac technology has the potential to monitor tumour motion and deformation using continuously acquired 2D cine MR images. In order to target tumours in their current shape and position the tumour outline must be established automatically. In this study we compared four automatic contouring algorithms that delineate the tumour in sequential cine MR images based on manually contoured training images.

Material and Methods

Five 1 min 2D cine MR images (Fig. 1) were acquired for two patients. Each sequence was split into a training set of ten source images and a test set of about 100 images. Method (1) is a multi-template matching, with a template taken from each source image centred on the tumour. For every test image the best position of each template is evaluated and the most similar match is selected. Method (2) uses a pulse-coupled neural network (PCNN) to improve the grey-value contrast between tumour and healthy tissue thus aiding the auto-contouring. The PCNN and associated erosion and dilation parameters were trained on the training sets using an accelerated particle swarm optimisation technique. For method (3) first the source image that is most similar to the current test image is selected. Then the source image is warped to the test image using an intensity driven B-spline registration. The last method, (4), uses image features (FAST/SIFT) to match distinct points of source and test images. The best source image is determined by the shortest mean descriptor distance. Residual misalignment is corrected for by a non-rigid transformation according to displacement vectors between matched features. All registration based methods (1,3,4) propagate contours according to the corresponding transformations.

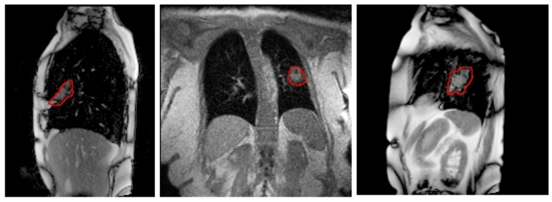

Fig 1.: Example slices of the cine MR images (bSSFP and GRE) acquired with a Siemens Aera 1.5T. The in-plane resolution is 2mm isotropic and the slice thickness is 5mm. Manually delineated tumour contours are depicted in red.

Results

Fig. 2 shows the averaged Dice coefficient and centroid distance, their standard deviation, and minimum / maximum value of the 5^{th}/95^{th} percentile of all cases after auto-contouring (1-4). Cases (w) and (b) represent the worst and best result, respectively, if only a single contour is propagated without considering motion. All methods improve the mean Dice overlap and centroid distance. Methods (1) and (3) achieve the best mean Dice score of 0.93 and a minimum 5^{th} percentile of 0.86 and 0.88 respectively. Method (2) produces the lowest mean centroid distance of 1.3mm, while maximum 95th percentile values range between 4.4mm (3) and 5.0mm (4). Training of the PCNN takes about 1 min based on 100 initialisation points and 20 iterations and the mean contouring times per image are (1) 1ms, (2) 24ms, (3) 518ms, and (4) 144ms.

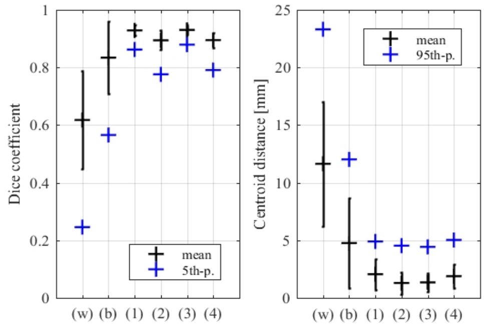

Fig. 2: Overlap evaluation results in terms of the Dice coefficient and the centroid distance. The mean values and the standard deviation for all five cases combined are given in black, whereas the global minimum 5th percentile of the Dice coefficient and maximum 95th percentile of the centroid distance are depicted in blue. Results without adapting the template contour to the test images are given for the worst case (w) and best case scenario (b). Application of methods (1) to (4) results in higher Dice coefficients and lower centroid distances.

Conclusion

Despite its simplicity multi-template matching (1) produces good results with low computational cost. Although, more sophisticated approaches (2,3,4) can handle unseen deformations, such flexibility - potentially required for longer image acquisitions or treatments - comes at the cost of robustness (2,4) or computational load (3).