AbstractID: 3671 Title: Machine Learning for the Geometry/Intensity Relationship in IMRT

Purpose:

We present a feasibility study for breast IMRT showing that, given enough training examples of patient CT images and corresponding plans, machine learning algorithms can predict a good plan for a new patient's geometry directly, without explicit numerical optimization and dose calculation.

Method and Materials:

From an expert's clinical plans for 22 patients, the features determining the optimized intensities were identified. We applied four machine learning algorithms (nonlinear regression, support-vector machines, k-nearest-neighbors, and barycentric interpolation) to automatically discover the relationship between the beamlet intensities and the input features on CT images. This was learned on a beamlet-by-beamlet basis to decrease the input and output dimensionality. Results were evaluated by comparing the predicted intensity and dose distributions to those from the clinical plan (ground truth).

Results:

First, the plan for each patient was learned from all remaining patients' plans. The average beamlet error (averaged over all patients) for the best method (support-vector) was -0.16%, with an average absolute error of 2.07%. D95 and D05 (97.1% and 105.3%, respectively), and V95 (97.6%) values for the support-vector method differed insignificantly from the expert's plans at the 5% significance level. A second experiment using smaller training sets and larger testing sets yielded an average error of 0.22% and an average absolute error of 2.27%, respectively, indicating that a few well-selected training datasets are adequate to learn the relationships. Plans could be predicted in <10 seconds.

Conclusion:

While the breast IMRT problem is relatively simple, this work indicates that machine learning has potential to ease the computational burden of IMRT in more complex sites (e.g. prostate, head and neck), where reducing the time for optimization parameter adjustment would be clinically beneficial.

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