Three dimensional dose prediction in proton therapy using artificial neural networks

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INTRODUCTION

Artificial Neural Networks (ANN) are a set of algorithms, inspired after the human brain. Knowledge-Based (KB) ANN have been used to generate dose models (DM) in stereotactic body radiation therapy (SBRT) [1-4]. ANN-based 3D dose modeling in proton therapy is novel. Intensity modulated proton therapy (IMPT) is a modern treatment method with highly conformal 3D dose distributions, which is especially beneficial for pediatric patients.

KB ANN is a hybrid learning system that maps problem-specific "domain theories" into neural networks and then refines this reformulated knowledge using backpropagation [5]. Treatment planning–specific knowledge or features are extracted form CT images, plan, structures, treatment protocols etc. and used to train KB ANN dose models (DM). A 3D dose prediction has two valuable uses 1) a quality control tool to evaluate the individual treatment plan quality against anticipated quality and 2) prospective evaluation of a proton dose distribution to identify if the patient should be referred for proton therapy.

AIM

Prospective dose prediction is a valuable quality-control tool in the treatment planning process. In the case of proton therapy, it also allows for fast prediction of whether a specific patient is more likely to benefit from advanced planning and delivery methods. We sought to develop a prototype, three-dimensional dose prediction tool for proton therapy using ANN.

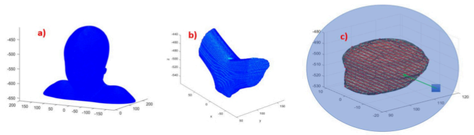

***Figure 1**. Example patient RT structures contoured on CT images. a) Patient skin, b) Beam path c) CTV structure with interior voxels in red. Voxels within 100 mm shaded area used in ANN training.*

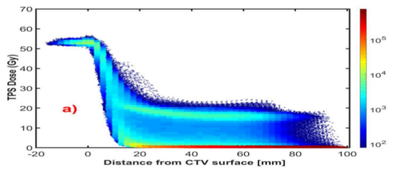

***Figure 2**. Scatter plots for pool of voxels for TPS dose values versus distance from the CTV surface. Distance is negative inside the CTV.*

METHOD

The data set used to develop our preliminary model included 24 pediatric patients with craniopharyngioma treated with pencil beam scanning (PBS) proton therapy. All patients received a total dose of 54 Cobalt Gray Equivalent (CGE) in 30 fractions. Treatment plans consisted of two lateral or oblique beams optimized using the Eclipse treatment planning system (TPS) (Varian Medical Systems, Inc., Palo Alto, CA).

Features from the treatment plan, structure set, and images were extracted for each voxel in the dose grid and pooled to train the ANN DM. The preliminary dataset was randomly divided with 70% used for training, 15% for validation and 15% for testing. Feed forward neural network models were trained with scaled conjugate gradient back propagation and a log-sigmoid activation function. In the first approach, two separate models were trained corresponding to ANN dose prediction within the clinical target volume (CTV) and outside of the CTV as in [1].

In the second approach, two ANN DMs were trained for voxels in the beam path and outside the beam path (Figure 1b). In the preliminary work, the existing beam path from prior treatment planning was used, though our goal is to generate a predicted beam path from the CTV structure and proton field characteristics. We used a total of 15 features, such as CT Hounsfield Units, distance from voxel to CTV, structure masks for chiasm, brainstem, optic nerves, structure volumes and others. The ANN model was trained with pooled voxel data to predict the dose in a new patient to assess whether the patient would benefit from treatment. Figure 1 shows triangulated skin (a), beam path (b) and CTV (c) structures. Only voxels within 100 mm of CTV were used in training (Figure 1c shaded area).

Figure 2 shows scatter plots of pooled voxel TPS dose versus distance from the CTV for two-beam IMPT treatment plans. The colorwash indicates the number of voxels on a logarithmic scale. Negative distances extend inside the CTV. MATLAB's ANN toolbox was used in dose modeling.

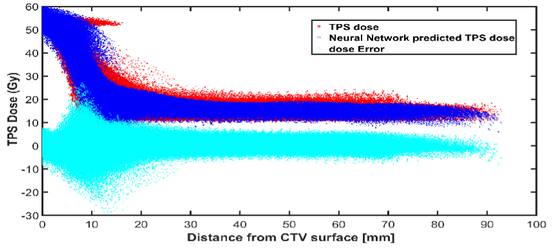

***Figure 3**. Voxel-wise target (red) and ANN predicted output (blue) and their differences (cyan) for dose distributions in the beam path structure versus distance from the CTV.*

RESULTS

Utilizing the first approach in which separate models were trained for regions inside the CTV and outside the CTV, the mean squared differences between ANN-predicted dose and the final TPS dose in the plan were 0.59 CGE and 1.96 CGE, respectively, for inside and outside of the CTV.

The average CTV dose and standard deviations for ANN 3D TPS-predicted dose were 53.0 CGE, and 0.3 CGE, respectively, corresponding to TPS doses of 53.0 CGE, and 0.5 CGE, respectively;

Figure 3 shows the voxel-wise results for the second approach in which models were trained separately inside and outside of the beam path. The mean squared differences between ANN predicted dose and the final TPS dose were 3.1 CGE and 0.69 CGE inside and outside of the beam path, respectively. The average CTV dose and standard deviations for ANN 3D TPS- predicted dose 51.5 CGE and 1.5 CGE in this second method of training.

Differences in the approaches were observed in the predicted dose within the CTV. The first approach results in a homogenous dose distribution inside the CTV while the second-approach dose falls in the middle of the CTV (Figure 3). Our first approach, however, fails to reproduce the beam dose outside the CTV (Figure 4c), while the second approach demonstrates better results (Figure 4 b)

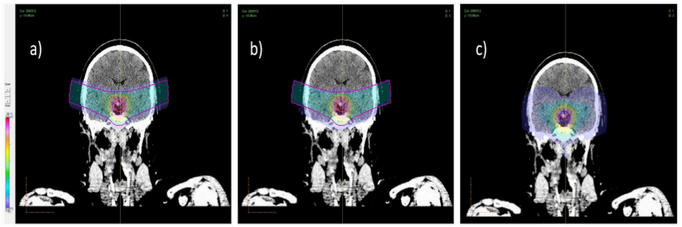

***Figure 4**. Original dose and ANN model–predicted dose/LETd distributions for a representative patient. a) TPS-calculated dose, b) ANN-TPS model prediction 2nd approach; c) ANN generated TPS dose from 1st approach*

CONCLUSIONS

We developed a prototype three-dimensional dose prediction algorithm for PBS proton therapy. Encouraged by these results, we intend to expand the validation and testing to include a total of 100 patients treated on the same protocol. To our knowledge, this the first use of ANN models to predict PBS proton therapy dose in 3-dimensions.

Our first approach, based heavily upon an SBRT model published in the literature[1], fails to adequately reproduce proton beam doses outside of the CTV. We suspect the limitation is due to a static beam delivery approach used in proton therapy contrasted with coplanar arcs used in the prior work reported by Campbell et al. Our second approach better predicts beam dose outside the CTV structure by utilizing a beam path mask to define in-field and out-of-field regions.

The results from both approaches suggest that combining these approaches by training the ANN in the CTV_T and outside the CTV but in beam path will likely result in better dose prediction.

Based on our early work with the ANN DM, we can generate dose predictions for a new patient with only the CT image and RT structure file. The developed model suggests that the tool could be clinically useful as quality control step as well as identifying which patients stand to benefit most from proton therapy. Future work will expand the data set used to train the model with the hope of improving dose prediction accuracy.

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