AI in Treatment Planning

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Potential Applications of AI in Treatment Planning

Ultimate Goal
(Outcome, Patient preference, Practicality, etc)
- Variation among physicians
- Art part of tx planning
- Outcome based planning
- Functional imaging and true dose painting

Physician Goal
(Physician’s perception based on experience, training, etc)
- Iterations between physician and dosimetrist
- Inefficiency/sub-optimal
- Dose/DVH prediction
- Pareto surface navigation
- DRL for parameter tuning

Planning Objectives
(Overly simplified mathematical modeling via dose)
AI for Treatment Planning

- Dose Distribution Prediction
3D Dose Prediction Using Deep Learning

- **Hypothesis**
  - Patients of similar medical conditions should have a similar relationship between optimal radiation dose and patient anatomy
  - This relationship can be learned with a deep neural network

- **Potential applications**
  - Treatment planning guidance
  - Automated treatment planning
  - Tradeoff navigation
  - Modality comparison
  - Patient consultation
  - Insurance approval

- **Technical barriers**
  - Different tumor sites, treatment protocols, treatment modalities, treatment machines, beam setups, energies, etc.
  - Different institutions, different physician/planner styles, etc.
  - General model versus model commissioning
A feasibility study for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning

Dan Nguyen, Troy Long, Xun Jia, Weiguo Lu, Xuejun Gu, Zohaib Iqbal, Steve Jiang
Dose Prediction – H&N VMAT w/ HD U-NET


Three-Dimensional Radiotherapy Dose Prediction on Head and Neck Cancer Patients with a Hierarchically Densely Connected U–net Deep Learning Architecture

Dan Nguyen, Xun Jia, David Sher, Mu–Han Lin, Zohaib Iqbal, Hui Liu, Steve Jiang
Dose Prediction - Variable Beam Angles

(9 channels: PTV & OARs)

Output 3D dose

Network (HD Unet)

(1 channel: sum-up of per-beam dose)

Anatomy Beam Model

Anatomy Only Model


Three–Dimensional Dose Prediction for Lung IMRT Patients with Deep Neural Networks: Robust Learning from Heterogeneous Beam Configurations

Ana M. Barragan–Montero, Dan Nguyen, Weiguo Lu, Mu–Han Lin, Xavier Geets, Edmond Sterpin, Steve Jiang
Dose Prediction - Differentiable DVH Approximation

- Human Domain Knowledge

\[
\text{Loss}_{DVH}(D_{true}, D_{pred}, M) := \frac{1}{n_s} \sum_s \frac{1}{n_b} \|D_{true}(M_s) - D_{pred}(M_s)\|_2^2
\]

- Learned Domain Knowledge

\[
\begin{align*}
\text{minimize } & \frac{1}{2} \|N_D(y_{true}) - b\|_2^2 + \frac{1}{2} \|N_D(N_G(x)) - a\|_2^2 \\
\text{minimize } & \frac{1}{2} \|N_D(N_G(x)) - c\|_2^2
\end{align*}
\]


Incorporating human and learned domain knowledge into training deep neural networks: A differentiable dose volume histogram and adversarial inspired framework for generating Pareto optimal dose distributions in radiation therapy

Dan Nguyen, Rafe McBeth, Azar Sadeghnejad Barkousaraie, Gyanendra Bohara, Chenyang Shen, Xun Jia, Steve Jiang
**Dose Prediction - Different Planner Styles**

<table>
<thead>
<tr>
<th>Dose Style</th>
<th>Name</th>
<th>Dataset</th>
<th>Training</th>
<th>Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Source</td>
<td>118</td>
<td>108</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Internal-A</td>
<td>34</td>
<td>29</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Internal-B</td>
<td>16</td>
<td>14</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Internal-C</td>
<td>20</td>
<td>17</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>External</td>
<td>60</td>
<td>20</td>
<td>40</td>
</tr>
</tbody>
</table>

**Dose Prediction with Deep Learning for Prostate Cancer Radiation Therapy: Adapting a Model to Different Treatment Planning Practices**

Roya Norouzi Kandalan\textsuperscript{a,b}, Dan Nguyen\textsuperscript{a}, Nima Hassan Rezaei\textsuperscript{a}, Ana M. Barragán-Montero\textsuperscript{a}, Sebastiaan Breedveld\textsuperscript{a}, Kamesh Namuduri\textsuperscript{b}, Steve Jiang\textsuperscript{c,d}, Mu-Han Lin\textsuperscript{e}
Dose Prediction – Uncertainty Estimation

- Monte Carlo Dropout
  - Use dropout during training AND inference
  - Effective performs variational inference from a Bernoulli distribution

Towards Safer Artificial Intelligence-Based Radiation Therapy Treatment Planning: Adding Uncertainty Estimation to Volumetric Dose Prediction Using An Approximate Bayesian Method On Deep Neural Networks

D Nguyen*, A Balagopal, A Sadeghnejad Barkousaraie, R McBeth, S Jiang, Medical Artificial Intelligence and Automation (MAIA) Laboratory, UT Southwestern Medical Center, Dallas, TX
Dose Prediction - Variable Desired Tradeoffs

Anatomy

Predicted Dose

Solid lines - desired
Dashed lines - predicted

© Jianhui Ma and Steve Jiang, Ph.D., MAIA Lab, 2018
Dose Prediction - Real Time Pareto Surface Navigation

Capable of predicting plans with 3% mean and max dose error (compared to optimized plan)

Prediction time: 0.6 seconds
Dose Prediction - Navigation w/ Beam Angles
AI for Treatment Planning
- *Hyper-parameter Tuning* w/ *DRL*
HDR Planning w/ DRL Based Organ Weight Tuning


Intelligent Inverse Treatment Planning via Deep Reinforcement Learning, a Proof–of–Principle Study in High Dose–rate Brachytherapy for Cervical Cancer

Chenyang Shen, Yesenia Gonzalez, Peter Klages, Nan Qin, Hyunuk Jung, Liyuan Chen, Dan Nguyen, Steve B. Jiang, Xun Jia
Operating a treatment planning system using a deep-reinforcement learning-based virtual treatment planner for prostate cancer intensity-modulated radiation therapy treatment planning

Chenyang Shen, Dan Nguyen, Liyuan Chen, Yesenia Gonzalez, Rafe McBeth, Nan Qin, Steve B. Jiang, Xun Jia

First published: 05 March 2020 | https://doi.org/10.1002/mp.14114
Hyper-Parameter Tuning w/ Human-Knowledge Guided DRL

- Standard DRL is inefficient in training because of searching for optimal policy randomly
- Human planner’s rule in operating a TPS generally works, but may not be optimal
- Human-knowledge guided DRL
  - Sample actions based on human knowledge
  - Allow random search to explore new policy
  - Substantial improvement in training efficiency
  - Better performance in treatment planning

Training time of KgTPN is only 8% of TPN

© Chenyang Shen, Ph.D. and Xun Jia, Ph.D., MAIA Lab, 2020
Hyper-Parameter Tuning w/ Hierarchical TP Network

- Standard DRL does not scale to actual planning cases
  - Network size of TPN grows with number of actions for a TPS linearly

- Hierarchical TPN (HieTPN)
  - A mathematically rigorous Hierarchical DRL framework to train HieTPN
  - Sequential decision making similar to a human
  - Network size does not grow with number of TPS actions

### Planning Performance of TPN and HieTPN

<table>
<thead>
<tr>
<th></th>
<th>PlanIQ score (TPN initial)</th>
<th>PlanIQ score (TPN-final)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TPN</strong></td>
<td>4.84 (±2.02)</td>
<td>8.44 (±0.48)</td>
</tr>
<tr>
<td><strong>HieTPN</strong></td>
<td>4.84 (±2.02)</td>
<td>8.62 (±0.83)</td>
</tr>
</tbody>
</table>
AI for Treatment Planning
- Dose Calculation
Dose Calculation using Deep Learning

- Deep learning can learn the difference between a simple and a sophisticated dose calculation method
  - scatter dose and inhomogeneity effort
- A completely different system is good for secondary dose check
- It can be used when real-time efficiency and reasonable accuracy are needed
  - Intermediate step dose calculation during plan optimization
  - Plan casting for online ART

<table>
<thead>
<tr>
<th>Patient</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gamma Index</td>
<td>1mm/1%</td>
<td>99.1%</td>
<td>99.9%</td>
<td>97.6%</td>
<td>99.8%</td>
<td>99.9%</td>
<td>99.9%</td>
<td>95.7%</td>
<td>96.3%</td>
<td>98.5%</td>
</tr>
<tr>
<td></td>
<td>2mm/2%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>99.7%</td>
<td>99.8%</td>
<td>99.9%</td>
</tr>
</tbody>
</table>


Xing, ..., Jiang, *Med Phys* 47(2)753-758, 2020

**Physics > Medical Physics**

*Submitted on 8 Aug 2019*

**A Feasibility Study on Deep Learning-Based Radiotherapy Dose Calculation**

Yixun Xing, Dan Nguyen, Weiguo Lu, Ming Yang, Steve Jiang
120 lung cases in Eclipse (72 training/18 validation/30 testing)
- Non-coplanar 3D CRT, 3D conformal arc, IMRT, and VMAT plans
- Rx dose: 24 Gy to 60 Gy
- Energy: 6 MV, 10 MV, 6xFFF, and 10xFFF

<table>
<thead>
<tr>
<th>Dose Maps</th>
<th>Gamma Pass rates</th>
<th>MSE</th>
<th>% of voxels over 3% dose diff of Rx dose</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2mm/2%</td>
<td>1mm/1%</td>
<td></td>
</tr>
<tr>
<td>Original AAA dose</td>
<td>(97.7±2.1)%</td>
<td>(86.0±9.8)%</td>
<td>0.52±0.26</td>
</tr>
<tr>
<td>Converted AXB dose</td>
<td>(99.9±0.4)%</td>
<td>(98.3±1.7)%</td>
<td>0.16±0.10</td>
</tr>
</tbody>
</table>

Xing, Zhang, ..., Jiang, JACMP DOI: 10.1002/acm2.12937, 2020

Boosting radiotherapy dose calculation accuracy with deep learning
Yixun Xing, Ph.D., You Zhang, Ph.D., Dan Nguyen, Ph.D., Mu-Han Lin, Ph.D., Weiguo Lu, Ph.D., Steve Jiang, Ph.D.
Convert PB Dose to MC Dose for Proton RT

- **MGH Data: Pencil Beam (XiO) → Monte Carlo (TOPAS)**

<table>
<thead>
<tr>
<th></th>
<th>HN</th>
<th>Liver</th>
<th>Prostate</th>
<th>Lung</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of patients</td>
<td>90</td>
<td>93</td>
<td>75</td>
<td>32</td>
</tr>
<tr>
<td>Number of beams</td>
<td>726</td>
<td>218</td>
<td>260</td>
<td>91</td>
</tr>
<tr>
<td>Pencil Beam vs MC</td>
<td>(73.3±6.3) %</td>
<td>(79.2±5.1) %</td>
<td>(73.3±2.7) %</td>
<td>(65.4±5.3) %</td>
</tr>
<tr>
<td>Predicted vs MC</td>
<td>(92.8±2.9) %</td>
<td>(92.7±2.9) %</td>
<td>(99.6±0.3) %</td>
<td>(89.7±3.8) %</td>
</tr>
</tbody>
</table>

Gamma index (1%/1 mm)


**Physics > Medical Physics**

[Submitted on 6 Apr 2020]

Improving Proton Dose Calculation Accuracy by Using Deep Learning

Chao Wu, Dan Nguyen, Yixun Xing, Ana Barragan Montero, Jan Schuemann, Haijiao Shang, Yuehu Pu, Steve Jiang
MC Denoising w/ Weakly SL and Lightweight CNN

- **Goal**
  - A DL denoising plugin to facilitate real-time MC dose calculation
  - ~100X efficiency improvement

- **Methods**
  - Weakly supervised learning for high training efficiency
  - A lightweight CNN for high inference efficiency

ucleus

- Relative MSE: 1.9% (WS); 1.8%(TS)
- Inference speed: ~80ms on one Tesla K80 GPU
AI for Treatment Planning

- Beam Angle Optimization
AI for Beam Orientation Optimization (BOO)

- Develop an AlphaGo type of DL algorithm
  - reinforcement learning (RL) policy network
  - Monte Carlo Tree Search (MCTS)
- Go movements → CyberKnife robot sequence

Ogunmolu, ..., Jiang, AAPM, 2018.
Use column generation (CG) to train a supervised learning (SL) policy network.

DeepBOO V1: Policy Network Trained w/ Column Generation


A Fast Deep Learning Approach for Beam Orientation Optimization for Prostate Cancer IMRT Treatments

Azar Sadeghnejad Barkousaraie, Olalekan Ogunmolu, Steve Jiang, Dan Nguyen
DeepBoo V2: Guided Monte Carlo Tree Search

- Policy network quickly generates a sampling probability at each level
- Tree builds its own policy over time
  - Search policy is updated as a weighted sum of NN policy and tree policy

A reinforcement learning application of guided Monte Carlo Tree Search algorithm for beam orientation selection in radiation therapy

Azar Sadeghnejad-Barkousaraie, Gyanendra Bohara, Steve Jiang, Dan Nguyen
DeepBoo V3: w/o the need of pre-dose calculation

- DNN is updating during the tree search after exploring each leaf
- No prior dose calculation is needed:
  - Using a pre-trained network to measure the quality of the treatment plan