

Treatment  
Planning in  
Radiation  
Therapy with  
AI and Soft  
Robots

Lekan  
Ogunmolu

Introduction

BOO

MCTS

BOO Motivation

Column Generation

ML-based  
Adaptive  
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Problem Setup

# Treatment Planning in Radiation Therapy with AI and Soft Robots

Lekan Ogunmolu

Perelman School of Medicine

University of Pennsylvania, Philadelphia, PA

February 04, 2021

# Talk Outline

Treatment Planning in Radiation Therapy with AI and Soft Robots

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- Beam Orientation Optimization (BOO)
  - Monte Carlo Tree Search and Neuro-Dynamic Programming for BOO
  - Column Generation as Pretraining for MCTS for BOO
- Patient Head Motion Correction in External Beam Radiation Therapy
  - Magnetic Resonance Imaging and Linear Accelerator Systems (MRI-LINACs)
  - Intensity-Modulated RT (IMRT): Earlier PhD Work
- Robustness Margins and Robust Deep Policies for Nonlinear Control

# Research Significance

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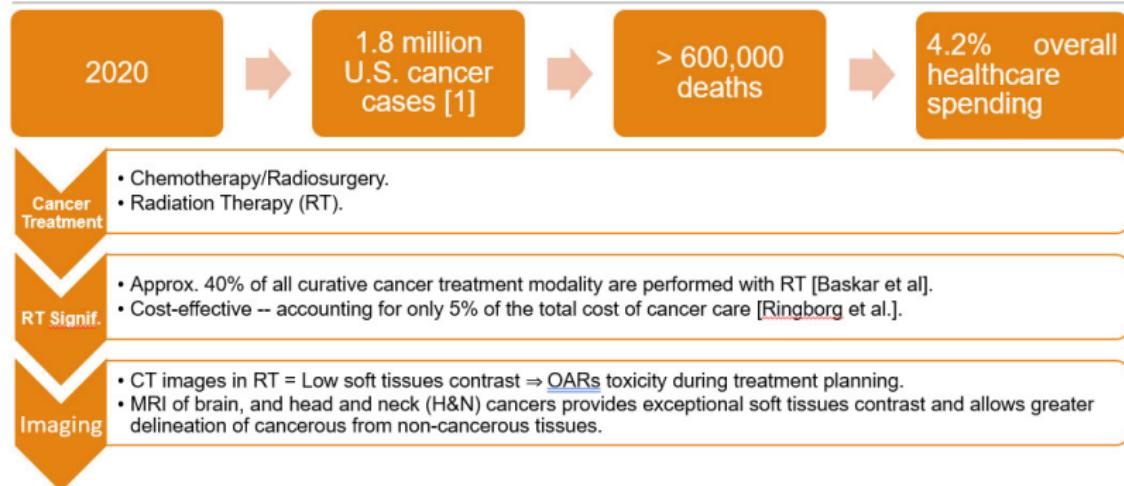
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# Part I.A: Beam Orientation Optimization (BOO)

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- Beam Orientation Optimization (BOO), and Head Stabilization in Radiation Therapy (RT)
  - Monte Carlo Tree Search and Neuro-Dynamic Programming for BOO

# Stereotactic Radiosurgery

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# External Beam RT

- External Beam RT is a widespread method for treating various cancer types.
- High-energy photons from a linear accelerator (LINAC) render cancerous cells necrotic.
- Excessive damage to healthy critical structures minimizes patient's quality of life.
- How to efficiently irradiate tumors while sparing organs-at-risk (OARs)?

# BOO Relevant Works

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- Ogunmolu, Olalekan, Michael Folkerts, Dan Nguyen, Nicholas Gans, and Steve Jiang. "Deep BOO! Automating Beam Orientation Optimization in Radiation Therapy." In *Algorithm Foundations of Robotics XIII*, Merida, Mexico. Published in *Springer's Proceedings in Advanced Robotics (SPAR) Book*, 2020.
- Barkousaraie, Azar Sadeghnejad, Olalekan Ogunmolu, Steve Jiang, and Dan Nguyen. "Using Supervised Learning and Guided Monte Carlo Tree Search for Beam Orientation Optimization in Radiation Therapy." In *Workshop on Artificial Intelligence in Radiation Therapy*, pp. 1-9. Springer, Cham, 2019.
- Azar Sadeghnejad Barkousaraie, Olalekan Ogunmolu, Steve Jiang, and Dan Nguyen. "A Fast Deep Learning Approach for Beam Orientation Selection Using Supervised Learning with Column Generation on IMRT Prostate Cancer Patients." *Medical Physics (AAPM)* 46 (6), E237-E237, San Antonio, TX, July 2019.
- Olalekan Ogunmolu, Azar Sadeghnejad Barkousaraie, Nicholas Gans, Steve Jiang, and Dan Nguyen. "An Approximate Policy Iteration Scheme for Beam Orientation Selection in Radiation Therapy." *Medical Physics (AAPM)* 46 (6), E386-E386 San Antonio, TX, July 2019.
- Azar Sadeghnejad Barkousaraie, Olalekan Ogunmolu, Steve Jiang, and Dan Nguyen. "A Reinforcement Learning Application of Guided Monte Carlo Tree Search Algorithm for Beam Orientation Selection in Radiation Therapy." *Medical Physics (AAPM)* 46 (6), E236-E236, San Antonio, TX, July 2019.

# Funding Agencies

- Cancer Prevention and Research Institute of Texas (CPRIT) (IIRA RP150485): \$858,356. PI: Steve Jiang
- CPRIT MIRA RP160661: \$4,103,894. PI: Steve Jiang
- NIH R-01 1R01CA237269-01: \$490,133. PI: Steve Jiang

# IMRT/Beam Orientation Optimization

- Intensity-modulated radiation therapy (IMRT) is one common EBRT method:
  - Delivers geometrically-shaped, high-precision photons
  - From different static beam orientations towards a planning target volume (PTV).
- BOO Problem: Determine best beam angle combinations for delivering radiation to a patient.
  - Essentially a combinatorial optimization problem.
  - Process of determining beamlets' intensities is termed **fluence map optimization** (FMO).

# IMRT/BOO Motivation

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- In most clinics, beam orientations are still manually chosen or adopted from a standard protocol for clinical use.
- Typical approaches leverage pre-solving the dose influence matrices for each beam orientation.
- Then solve FMO.
- Time consuming (hours for dose fluence), and minutes for (FMO); Still solution is often not optimal.

# Current Approaches

- Stochastic optimization approaches: simulated annealing; genetic algorithms and gradient search, or a combination of genetic and gradient search algorithms.
- Mixed-integer programming, branch and cut/bound algorithms, beam angle elimination algorithms.
- Commercial planners use some highly non-convex objective (actual function is proprietary and unknown to public).

# BOO Flowchart

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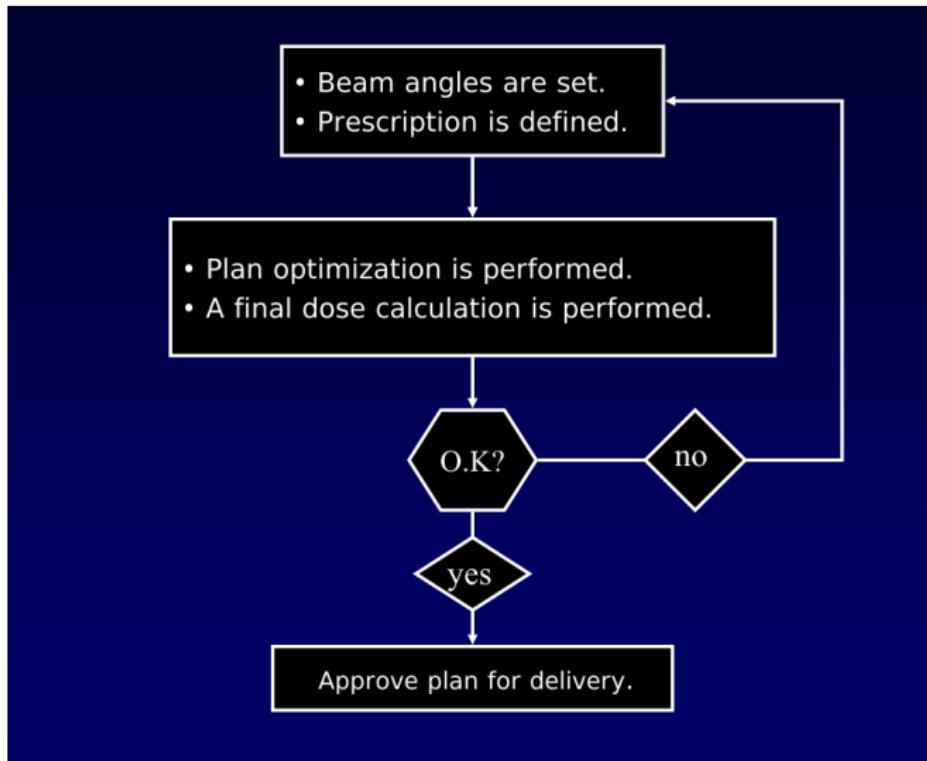
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Reprinted from "IMRT Optimization Algorithms. David Shepard. Swedish Cancer Institute. AAPM 2007."

# Contributions

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## WAFR '18 Paper

Ogunmolu, Olalekan, Michael Folkerts, Dan Nguyen, Nicholas Gans, and Steve Jiang. "Deep BOO! Automating Beam Orientation Optimization in Radiation Therapy." In *Algorithm Foundations of Robotics XIII*, Merida, Mexico. Published in *Springer's Proceedings in Advanced Robotics (SPAR) Book*, 2020.

- A sparse tree lookout strategy for games with large state spaces guides transition between beam angle sets
- Tree lookout strategy guided by a deep neural network policy

# What have we wrought?

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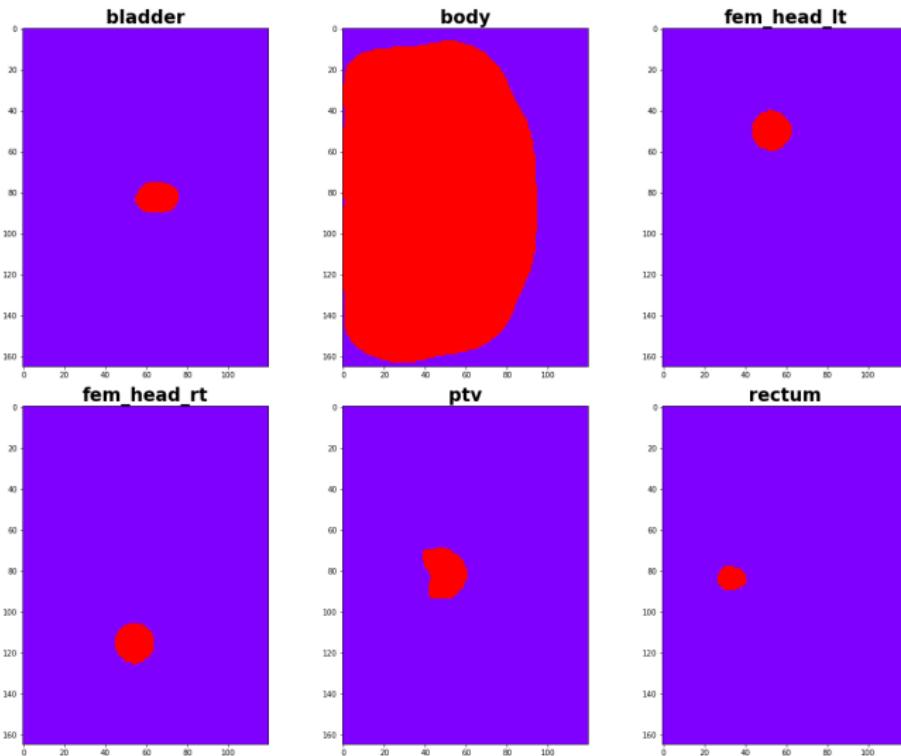
Problem Setup

- Network generates a policy that guides MCTS simulations for two players in a zero-sum Markov game
  - Produces a *utility (value) function* & a subjective *probability distribution*
- Each player in a two-player Markov game finds an alternating best response to the current player's average strategy
  - driving the neural network policy's weights toward an approximate **saddle equilibrium** [Heinrich et al. (2015)].
  - aids network in finding an *approximately optimal* beam angle candidate set that meets a dosimetric requirements.

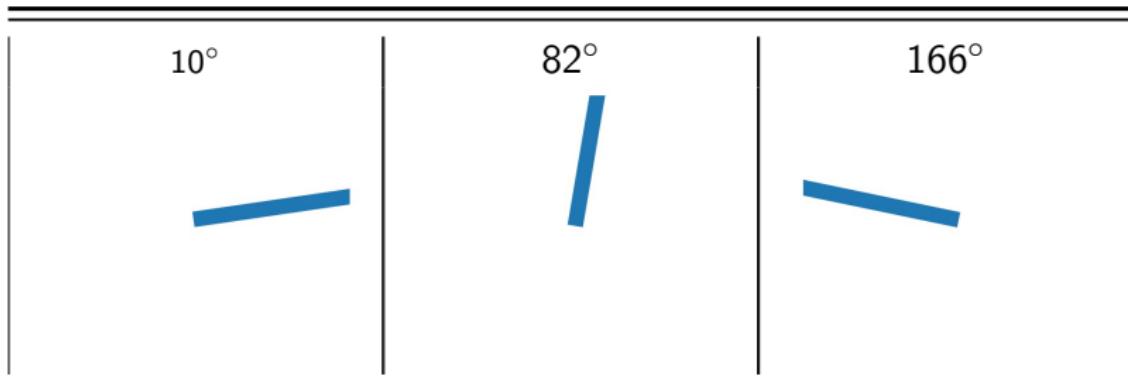
# Data Preprocessing

- 77 anonymized patient CT scans,  $D$ , and their dose influence matrices,  $\mathcal{D}_{ij}$
- Scans shaped,  $D \times N \times H \times W$  from prostate cases in previous treatment plans
- Each slice resized to  $64 \times 64$

# State Representation: Prostate Organ Masks



# State Representation: Beam Angles



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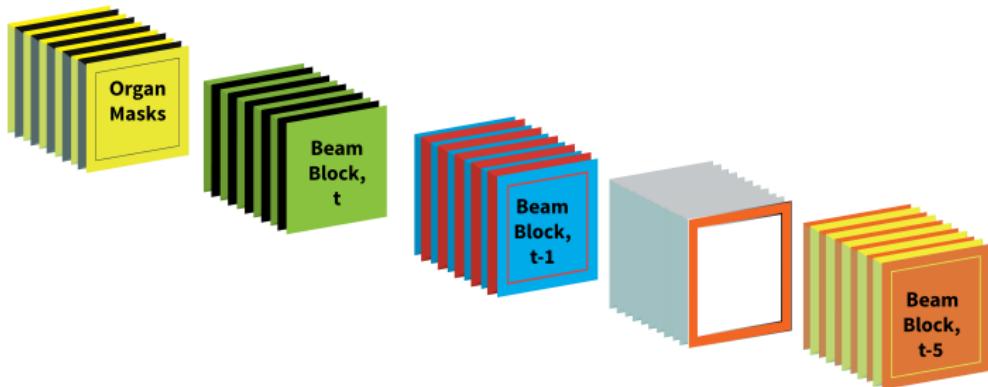
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# State Representation



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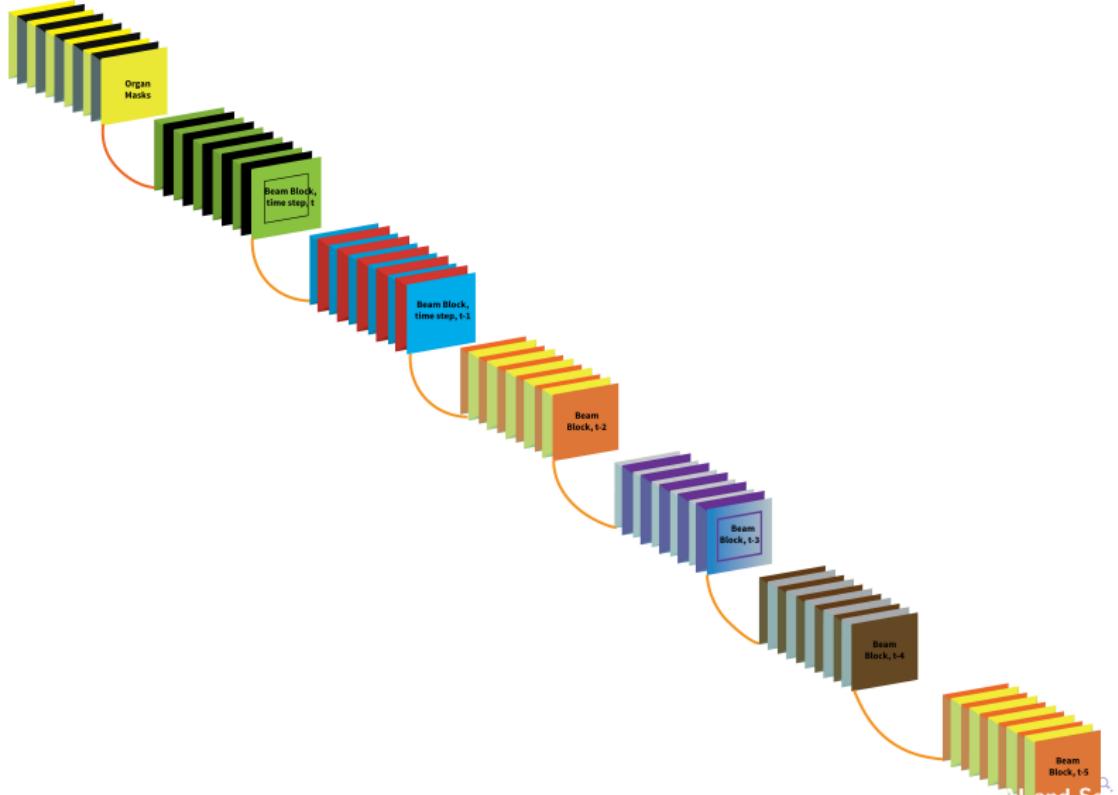
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# Tree Composition

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Every **node** of the tree,  $x$ , has the following fields:

- a pointer to the parent that led to it,  $x.p$ ;
- the beamlets,  $x_b$ , stored at that node;  $b = \{1, \dots, m\}$ ;
- a set of move probabilities prior,  $p(s, a)$ ;
- a pointer  $x.r$ , to the reward  $r_t$ , for the state  $x_t$ ;
- a pointer to the state-action value  $Q(s, a)$  and its upper confidence bound  $U(s, a)$ ;
- a visit count  $N(s, a)$ , that indicates the number of times that node was visited; and
- a pointer  $x.child$ ; to each of its children nodes.

# Two-Player MCTS Training Framework

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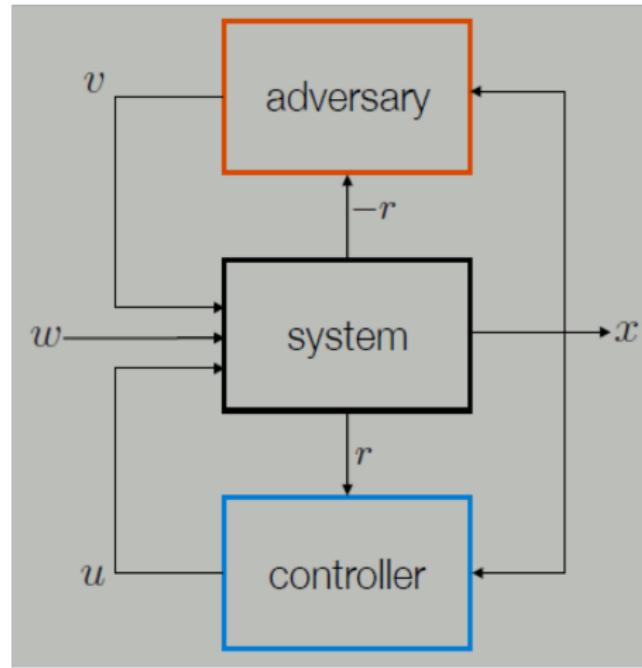
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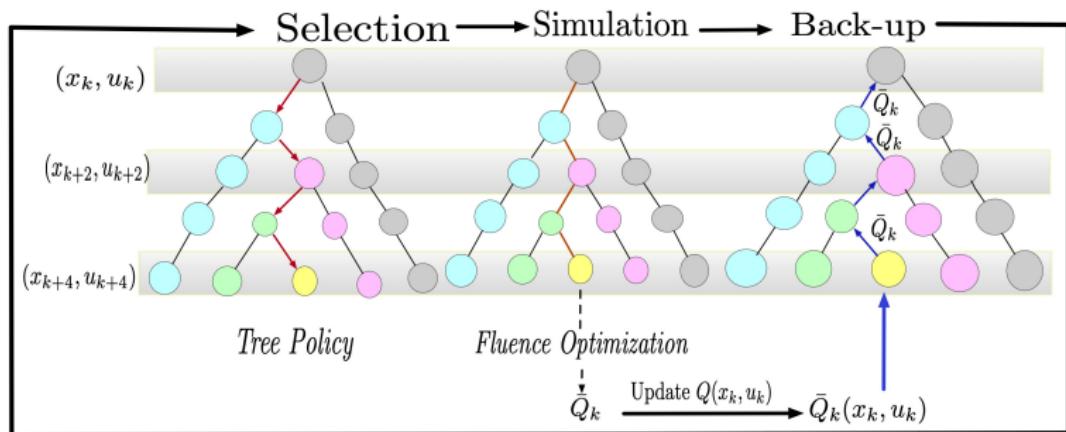
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# Game Simulation



# Game Tree Simulation

- Network roll-out policy then guides the tree's game toward a *best-first* set of beam angle candidates
- Best-first leaf node encountered is the child node with the highest reward in the tree
- Focuses learning on regions of the state space that are likely to have a good fluence

# Mixed Strategies

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- Each player,  $p_1, p_2$ , bases its decision on a random event's outcome
  - generating a **mixed strategy** determined by **averaging the outcome** of individual plays.
- Both players constitute a two-player **stochastic action selection strategy**:  $\pi(s, a) = Pr(a|s) := \{\pi^{p_1}, \pi^{p_2}\}$  that gives the probability of selecting moves in any given state
- Suppose the game simulation starts from an initial condition  $s_0$ .

# Saddle Point Strategy Formulation

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- The **saddle point strategies** for an optimal control sequence pair  $\{a_t^{p_1^*}, a_t^{p_2^*}\}$  can be recursively obtained by optimizing a state-action value cost,  $\mathcal{J}_t(s, a)$

$$V_t^*(s) = Q_t^*(s_t, \pi_t^{p_1}, \pi_t^{p_2}) = \min_{\pi^{p_1} \in \Pi^{p_1}} \max_{\pi^{p_2} \in \Pi^{p_2}} Q_t^*(s_t, \pi^{p_1}, \pi^{p_2}) \\ \forall s_t \in \mathcal{S}, \pi^{p_1} \in \Pi^{p_1}, \pi^{p_2} \in \Pi^{p_2}.$$

such that

$$v_{p_1}^* \leq v^* \leq v_{p_2}^* \quad \forall \{\pi_t^{p_1}, \pi_t^{p_2}\}_{0 \leq t \leq T}.$$

where  $v_{p_i}^*$  are the respective optimal values for each player.

# Methods: Search

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- $Q$ -value defined as

$$\bar{Q}(s, a) = Q_j(s, a) + c \sqrt{\frac{2 \ln n(s)}{N(s, a)}}, \quad (1)$$

$$a^* = \arg \max_a \bar{Q}(s, a) \quad (2)$$

---

## Fluence Map Optimization

- Suppose  $\mathcal{X}$  is the total discretized of voxels of interest ( $VOI's$ ) in a target volume
- Let  $\mathcal{B}_1 \cup \mathcal{B}_2 \cup \dots \cup \mathcal{B}_n \subseteq \mathcal{B}$  represents the partition subset of a beam  $\mathcal{B}$ ,

# Methods: FMO problem definition

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- The pre-calculated dose term is given by

$$\mathbf{Ax} = \left\{ \sum_s \frac{w_s}{v_s} \mathcal{D}_{ij}^s \mathbf{x}_s \mid \mathcal{D}_{ij} \in \mathbb{R}^{n \times l}, n > l \right\}$$

- Let  $w_s = \{\underline{w}_s, \bar{w}_s\}$  be the respective underdosing and overdosing weights for the OARs and PTVs
- We propose the following cost

$$\frac{1}{w_s} \sum_{s \in \text{OARs}} \|(\mathbf{b}_s - \underline{w}_s \mathcal{D}_{ij}^s \mathbf{x}_s)_+\|_2^2 + \frac{1}{v_s} \sum_{s \in \text{PTVs}} \|(\bar{w}_s \mathcal{D}_{ij}^s \mathbf{x}_s - \mathbf{b}_s)_+\|_2^2 \quad (3)$$

# Methods: FMO

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- Rewriting the objective, subject to nonnegative pixel intensity constraints, we have the minimization problem

$$\min \frac{1}{2} \|Ax - b\|_2^2 \quad \text{subject to } x \geq 0.$$

- The Lagrangian becomes

$$L(x, \lambda) = \min \frac{1}{2} \|Ax - b\|_2^2 - \lambda^T x.$$

- Introducing an auxiliary variable  $z$ , we have

$$\min_x \frac{1}{2} \|Ax - b\|_2^2, \quad \text{subject to } z = x, \quad z \geq 0,$$

# Methods: FMO by way of ADMM

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- Solving either the  $\mathbf{x}$  and  $\mathbf{z}$  sub-problems, we have

$$\mathbf{x}^{k+1} = (\mathbf{A}^T \mathbf{A} + \rho \mathbf{I})^{-1} (\mathbf{A}^T \mathbf{b} + \rho \mathbf{z}^k - \boldsymbol{\lambda}^k). \quad (4)$$

- And using the soft-thresholding operator,  $S_{\boldsymbol{\lambda}/\rho}$ , we find that

$$\mathbf{z}^{k+1} = S_{\boldsymbol{\lambda}/\rho} (\mathbf{x}^{k+1} + \boldsymbol{\lambda}^k), \quad (5)$$

where  $S_{\boldsymbol{\lambda}/\rho}(\tau) = (\mathbf{x} - \boldsymbol{\lambda}/\rho)_+ - (-\tau - \boldsymbol{\lambda}/\rho)_+$ .  $\boldsymbol{\lambda}$  is updated as

$$\boldsymbol{\lambda}^{k+1} = \boldsymbol{\lambda}^k - \gamma (\mathbf{z}^{k+1} - \mathbf{x}^{k+1}), \quad (6)$$

where  $\gamma$  is a parameter that controls the step length.

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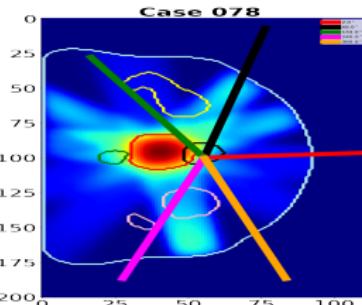
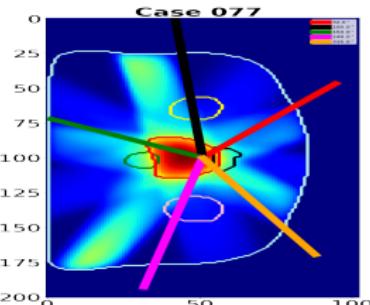
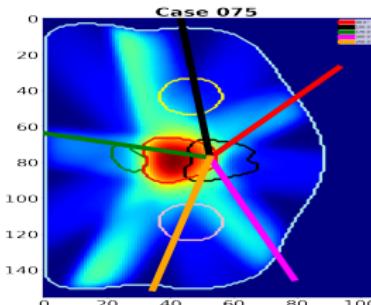
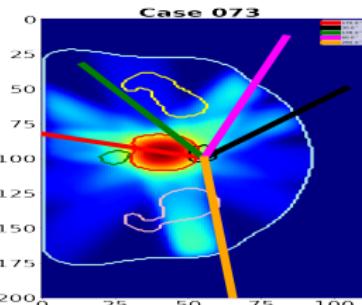
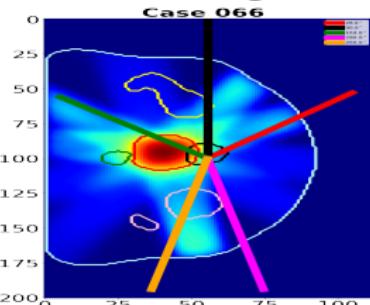
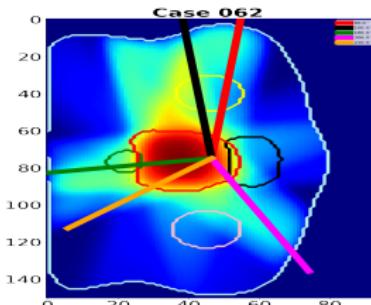
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## Dose washes for select patients during testing of self-play network

### Inference Regime



# Dose Volume Histograms

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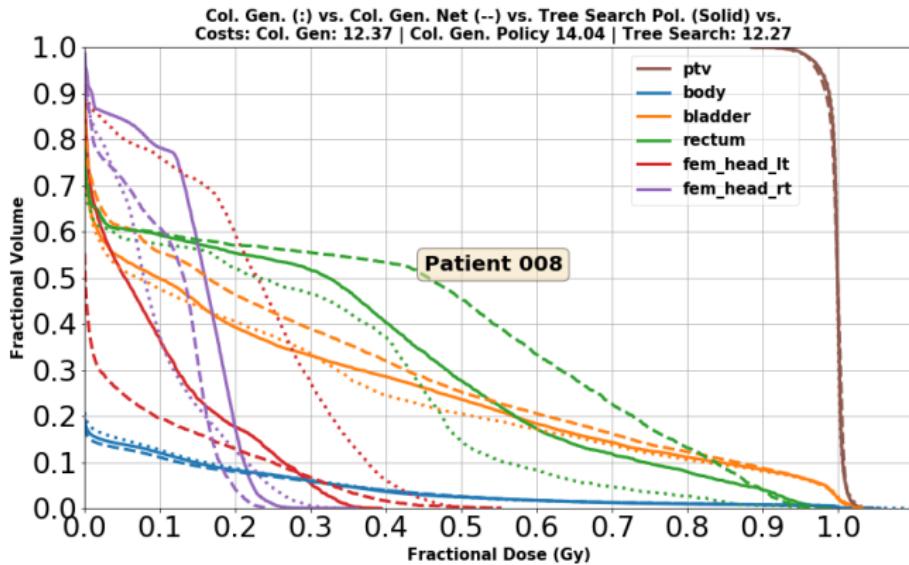
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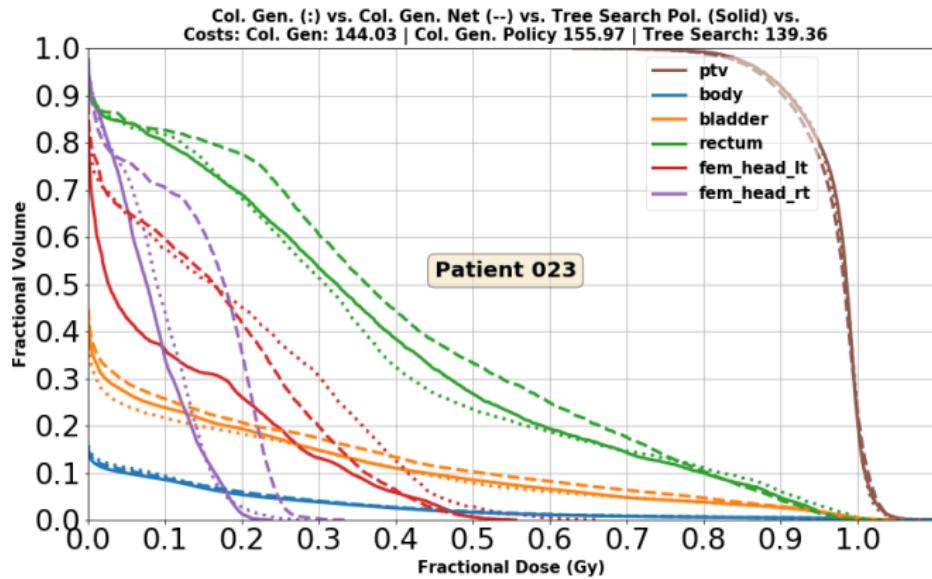
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# Discussions

- The policy selects fairly equidistant beams
- Yields wash plots that provide good dosimetric concentration on the tumor
- Gives sharp gradients at transition between tumors and OARs
- Largely avoids strong dose to OARs
- Finding the good beam angle candidates is orders of magnitude faster than the current approaches
- Beam angles prediction now takes between 2-3 minutes before we settle on a good candidate beam angle set.

# Conclusions

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- Finding the good beam angle candidates is orders of magnitude faster than the current approaches
  - Based on a neural network generative model of an MDP
  - Sparse lookahead search builds tree with nodes labeled by state-action pairs in an alternating manner (2-3 minutes).
  - Tree built stagewise from root to nodes has fixed depth; sample rewards stored on edges connecting state-action with state nodes
- Beam angles prediction now takes between 2-3 minutes before we settle on a good candidate beam angle set.

# Part I.B: Supervised Column Generation Pretraining for BOO

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- Beam Orientation Optimization (BOO), and Head Stabilization in Radiation Therapy (RT)
  - Column Generation as Pretraining for Deep Neural Network BOO

# Relevant Publications

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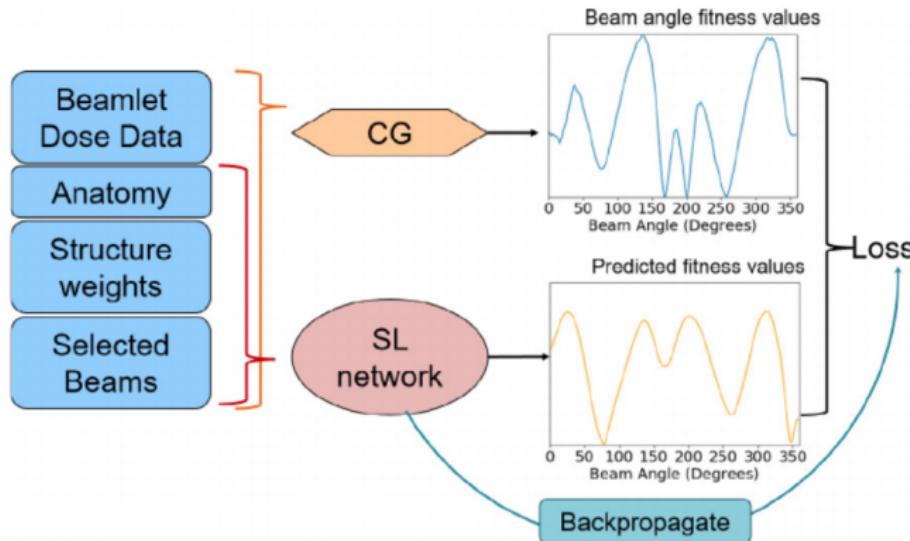
# Goals

- Fast+Flexible DNN BOO Solution in seconds
- Application to clinical routines for treatment planning acceleration
- Patient's anatomy  $\Leftrightarrow$  Optimal Beam Orientations  $\Leftrightarrow$  Optimization algorithm
- Data Preparation as WAFR '18 paper + augmentation + random OAR weight generation = 30,800 samples for training, validation and testing proposed DNN algorithm.
- Greedy iterative column generation algorithm for finding optimal beam set.

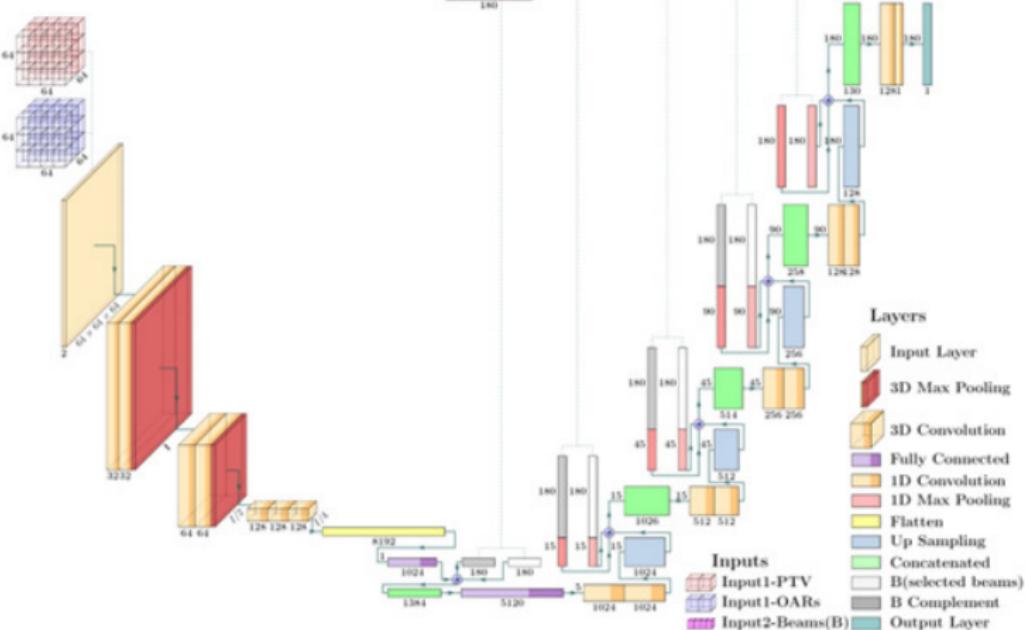
# Training Overview

- From an empty beam set
  - Iteratively add a beam with the greatest likelihood to improve the current FMO solution
  - FMO leverages Chambolle-Pock first-order primal-dual proximal operator on GPU
  - DNN then trained to learn beam orientation reasoning of CG
- DNN essentially internalizes the FMO solution via CG.s

# Training Schematic



# Network Structure



# Loss Table

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Problem Setup

Fold #	1	2	3	4	5	6	Total <sup>a</sup>
Train best <sup>b</sup>	0.50%	0.63%	0.62%	0.68%	0.53%	0.78%	0.62 ± 0.09%
Validation best <sup>c</sup>	0.91%	1.04%	1.06%	1.06%	1.12%	1.06%	1.04 ± 0.06%
Test best <sup>d</sup>	1.39%	1.44%	1.50%	1.30%	1.39%	1.64%	1.44 ± 0.11%
Training last <sup>e</sup>	0.62%	0.52%	0.63%	0.63%	0.53%	0.50%	0.57 ± 0.06%
Validation last <sup>f</sup>	1.92%	1.17%	2.54%	2.49%	2.62%	2.18%	2.15 ± 0.50%
Test last <sup>g</sup>	1.59%	1.54%	1.73%	1.79%	1.68%	1.65%	1.66 ± 0.08%
Best epoch number	374	303	189	272	387	165	

*Average training, validation, and test loss functions (MSE%) at different epochs for the full network.*

# Inference: Column Generation vs U-Net

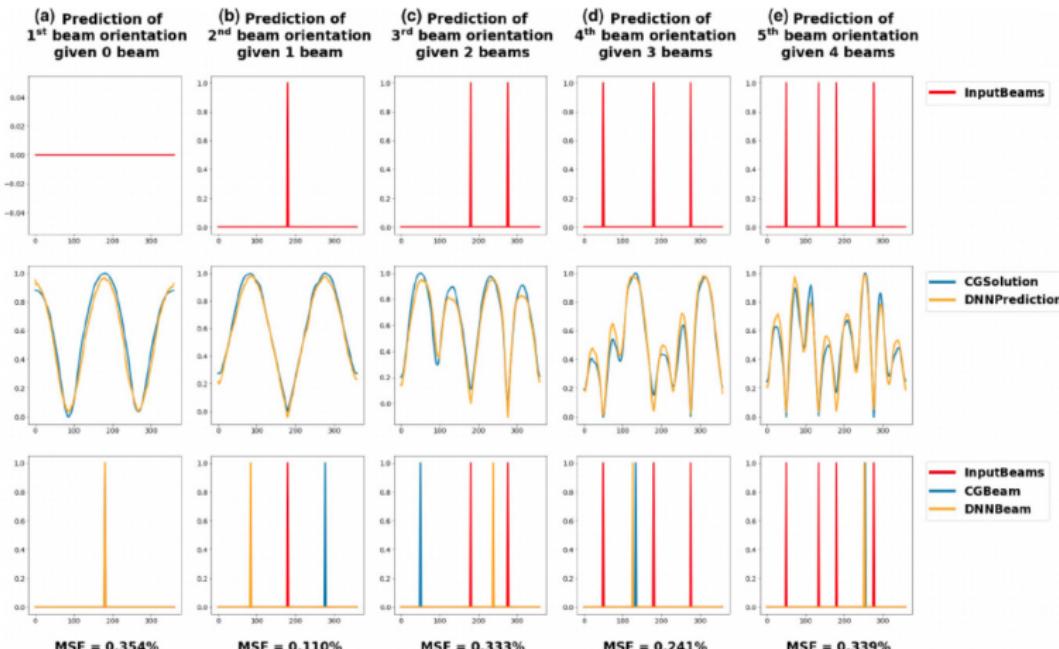
Treatment Planning in Radiation Therapy with AI and Soft Robots

Lekan Ogunmolu

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- (a) Prediction of 1st beam orientation given no beam. (b) Prediction of 2nd beam orientation given 1 beam.  
(c) Prediction of 3rd beam orientation given 2 beams. (d) Prediction of 4th beam orientation given 3 beams.  
(e) Prediction of 5th beam orientation given 4 beams.

# DVH of Column Generation vs Neural Network

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Lekan Ogunmolu

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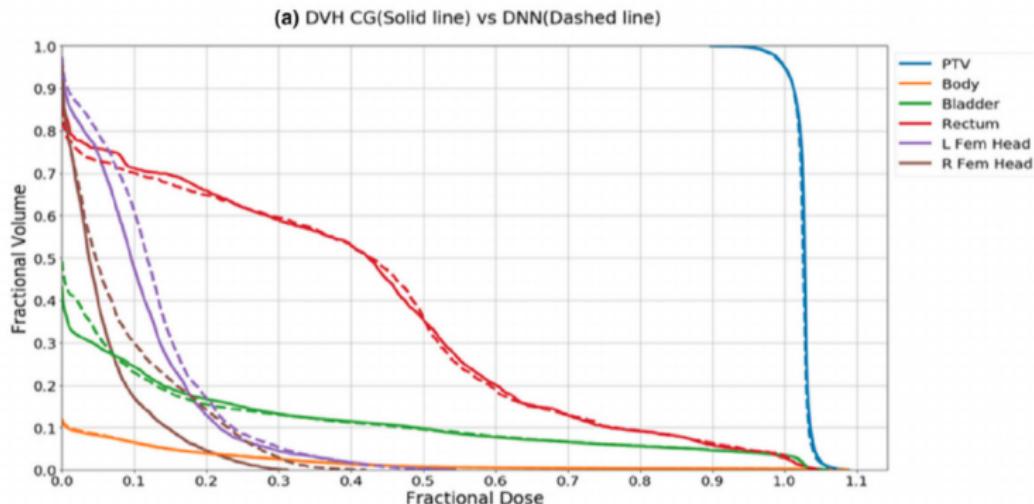
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# Dose Washes of Column Generation vs Neural Network

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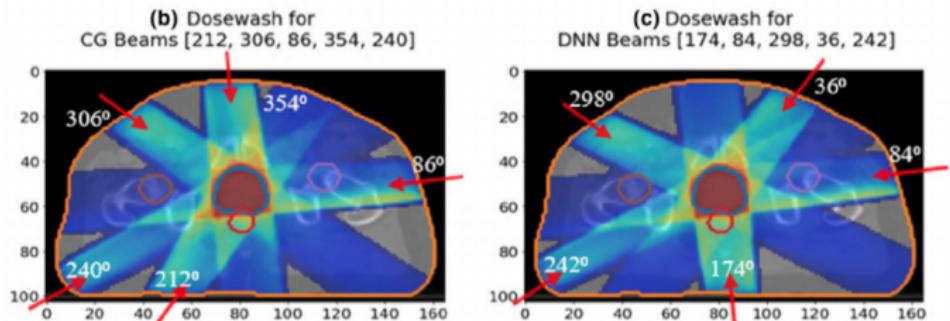
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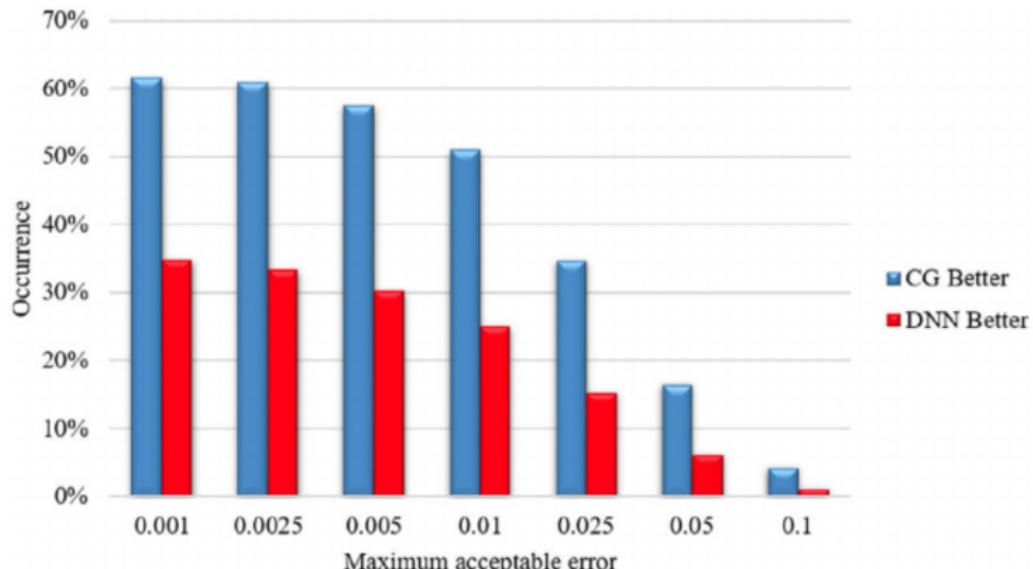
Approach

Problem Setup



Dose-Volume Histogram of CG vs DNN architectures

# FMO Costs: Column Generation vs Neural Network



Dose-Volume Histogram of CG vs DNN architectures

# Conclusions

- A Sparse Lookout Tree Strategy for guiding beam angle transitions while training a neural network
- A supervised deep neural network that learns from a CG algorithm
- Both methods leverage the convex FMO in learning the *optimal* set of beam angles
  - Alternating Direction Method of Multipliers
  - Chambolle-Pock algorithm
- Trade-offs in solutions generated by either approach allows flexibility for treatment planners
- Grants
  - Cancer Prevention and Research Institute of Texas (CPRIT) (IIRA RP150485): \$858,356. PI: Steve Jiang
  - CPRIT MIRA RP160661: \$4,103,894. PI: Steve Jiang
  - NIH R-01 1R01CA237269-01: \$490,133. PI: Steve Jiang

# Part II.A: Head Stabilization in RT

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Problem Setup

- Head Stabilization in Cancer Radiation Therapy
  - Magnetic Resonance Imaging-Linear Accelerator Systems (MRI-LINACs)
- Funding Sources
  - NIH-R01. PI: Rodney Wiersma
  - UT Southwestern Medical Center: PI: Steve Jiang and Nick Gans

# Robotic Radiosurgery

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## A Patient Head Motion-Correction Mechanism for MRI-LINAC RT

OLAKEGAN OGUNMOLU

DEPARTMENT OF RADIATION ONCOLOGY, PENN SCHOOL OF MEDICINE

- Current Collaborators: Rodney Wiersma & Xinmin Liu (UChicago → UPenn)
- Past Collaborators: Steve Jiang, Xuejun Gu, (UT Southwestern); Nick Gans (UT Dallas, UT Arlington)

# Relevant Publications

- Ogunmolu, Olalekan, Xinmin Liu, Nicholas Gans, and Rodney D. Wiersma. "Mechanism and Model of a Soft Robot for Head Stabilization in Cancer Radiation Therapy." In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 4609-4615. IEEE, 2020.
- Ogunmolu, Olalekan, and Rodney D. Wiersma. "Kinematics and Kinetics of a Continuum Parallel Soft Robot for MRI-LINAC Motion Correction." Working Paper, In *IEEE Transactions on Robotics*, IEEE 2020.
- Ogunmolu, Olalekan and Rodney D. Wiersma. "A Real-Time Patient Head Motion Correction Mechanism for MRI-Linac Systems." In *2020 Virtual Joint AAPM/COMP Meeting*, AAPM 2020.
- Ogunmolu, Olalekan, Xinmin Liu, Rodney D. Wiersma. "Auto-Determination of the Dextrous WorkSpace in Robotic Stereotactic Radiosurgery." In *2020 Virtual Joint AAPM/COMP Meeting*, AAPM 2020.

# Correcting Head Motion: Existing Techniques

Treatment Planning in Radiation Therapy with AI and Soft Robots

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(a)



(b)



(c)



(d)



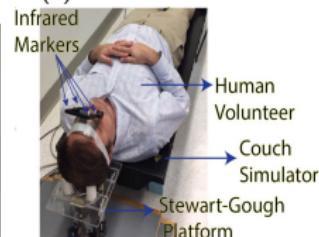
(e)



(f)



(g)



(h)

(a) The BRW SRS Frame [Chelvarajah et al. (2004)], (b) A thermoplastic face mask (c) Gamma Knife, (d) Accuray<sup>®</sup> Inc's Cyberknife (e) The Ostyn robot (f) Frame With MRI Coils [Courtesy of PSOM], (g) Wiersma Platform [Belcher (2017)], (h) Motion Compensation with the Wiersma Stewart-Gough Platform [Ogunmolu and Wiersma (2020)].

# MRI-LINAC

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# Proposal: External Beam RT with Soft Robots

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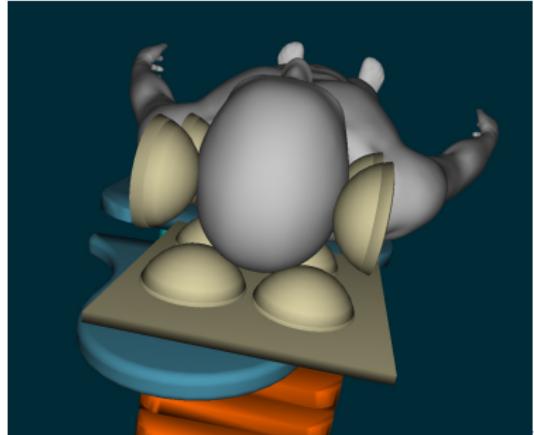
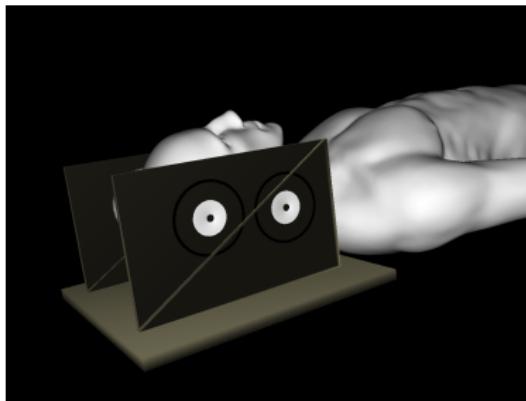
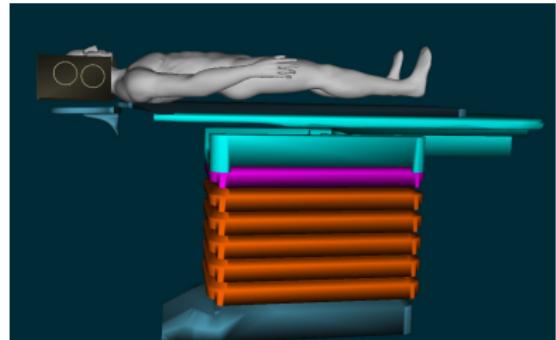
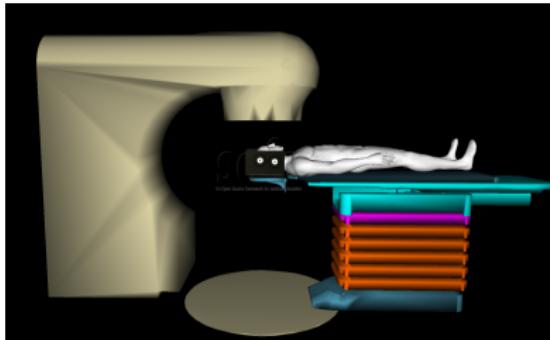
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# Cephalopods-inspired CCOARSE Actuator Design

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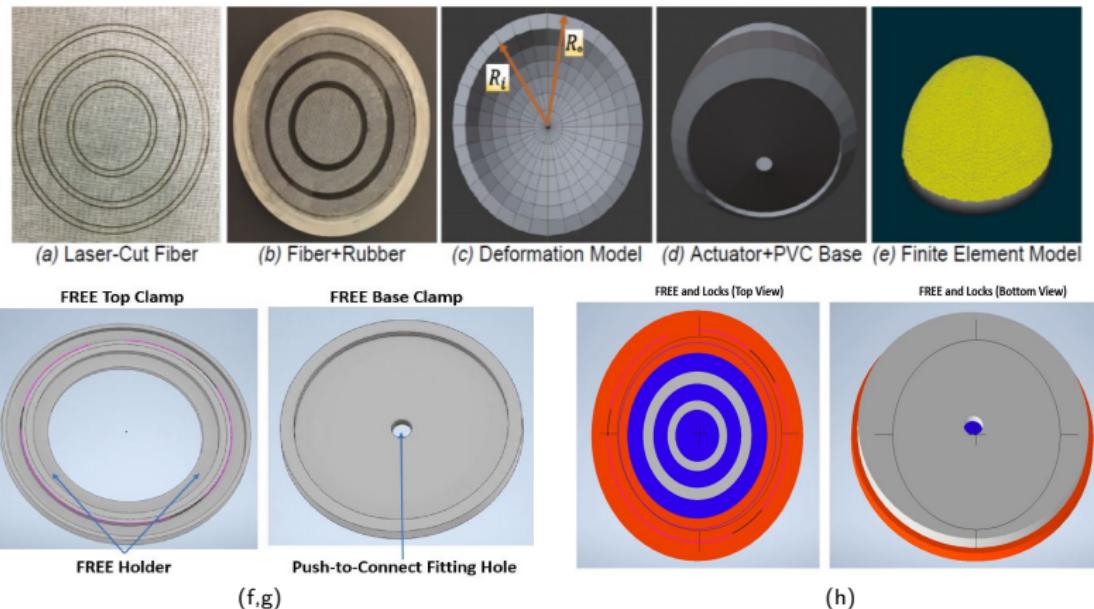
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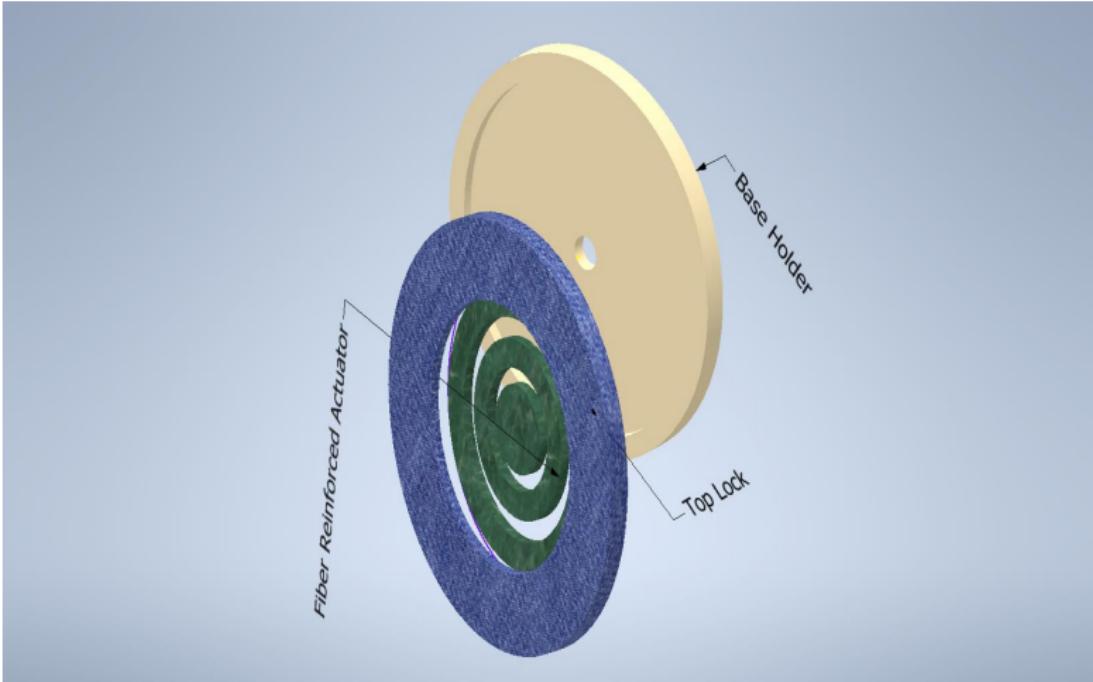
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# Cephalopods-inspired CCOARSE Actuator Design



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# Pneumatic Actuation/Control Scheme

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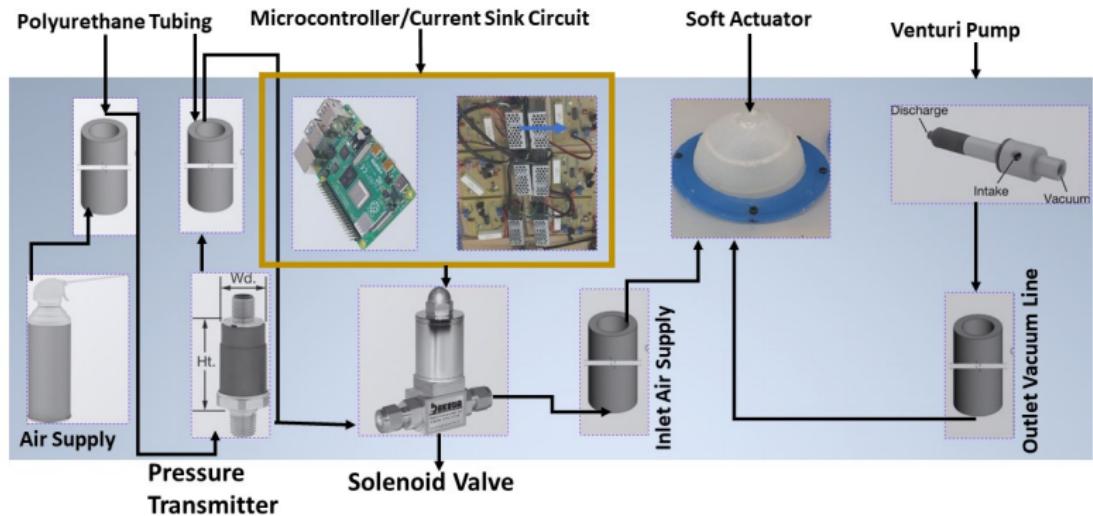
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# Nonlinear Elastic Deformation Analysis

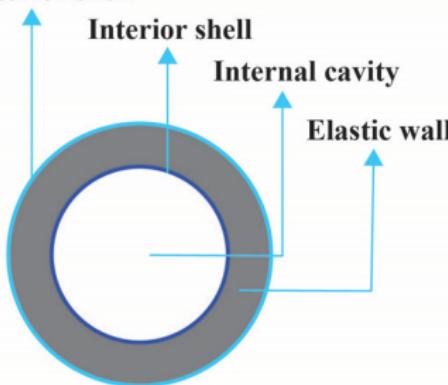
## IAB SHELLS AND AIR CAVITY/DEFORMATION ANALYSIS

Exterior shell

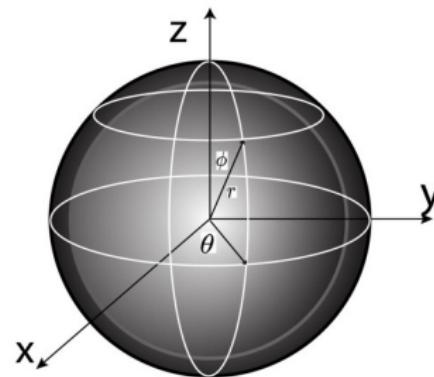
Interior shell

Internal cavity

Elastic wall



$(r, \phi, \theta)$



$$r_i \leq r \leq r_o, \quad 0 \leq \theta \leq 2\pi, \quad 0 \leq \phi \leq \pi$$

# Soft IK via Boundary Value Problem

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- Using the following boundary conditions for the Cauchy Stress,
  - $\sigma_{rr}|_{R=R_0} = -P_{atm}, \sigma_{rr}|_{R=R_i} = -P_{atm} - P$
- And together with Cauchy's first law, we find that
  - $\sigma_{rr}(r) = - \int_{r_i}^{r_o} [2C_1\left(\frac{r}{R^2} - \frac{R^4}{r^5}\right) + 2C_2\left(\frac{r^3}{R^4} - \frac{R^2}{r^3}\right)] dr$
  - $\sigma_{rr}(r) = \int_{R_i}^{R_o} [2C_1\left(\frac{1}{r} - \frac{R^6}{r^7}\right) - 2C_2\left(\frac{R^4}{r^5} - \frac{r}{R^2}\right)] dr$
- With  $\sigma_{rr}|_{R=R_i} = -P_{atm} - P$  and setting  $P_{atm} = 0$ , we find
  - $P(r) = \int_{r_i}^{r_o} [2C_1\left(\frac{r}{R^2} - \frac{R^4}{r^5}\right) + 2C_2\left(\frac{r^3}{R^4} - \frac{R^2}{r^3}\right)] dr$
  - $P(r) = \int_{R_i}^{R_o} [2C_1\left(\frac{1}{r} - \frac{R^6}{r^7}\right) - 2C_2\left(\frac{R^4}{r^5} - \frac{r}{R^2}\right)] dr$
  - $r^3 = R^3 + r_i^3 - R_i^3 \text{ and } r_o^3 = R_0^3 + r_i^3 - R_i^3$

# Volumetric Deformation Results (Simulation)

Treatment Planning in Radiation Therapy with AI and Soft Robots

Lekan Ogunmolu

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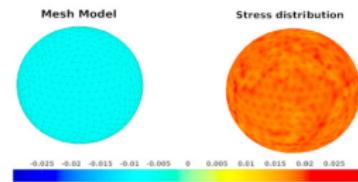
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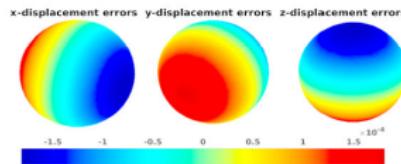
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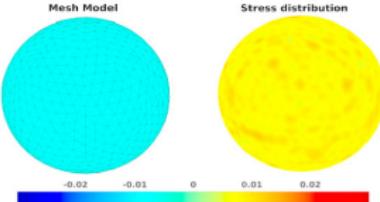
(a) Left: Mesh model. Right: Stress distribution on outer skin.



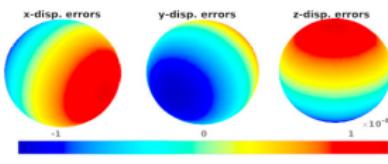
(b) Displacement errors along  $x, y, z$  coordinates.

Inputs				Outputs			
$C_1$	$C_2$	$R_i$	$r_i$	$R_o$	$r_o$	$P$	$\Delta V$
1.1e4	2.2e4	.027	.03	.03	.033	.76	$\approx 0$

Fig. 6: Volumetric Deformation (Expansion).



(a) Left: Mesh model. Right: Stress distribution on outer skin.



(b) Displacement errors along  $x, y, z$  coordinates.

Inputs				Outputs			
$C_1$	$C_2$	$R_i$	$r_i$	$R_o$	$r_o$	$P$	$\Delta V$
1.1e4	2.2e4	.025	.03	.03	.028	-.34	$\approx 0$

Fig. 7: Volumetric Deformation (Compression).

# Volumetric Deformation Results (Actual)

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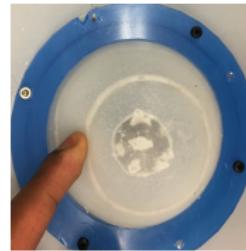
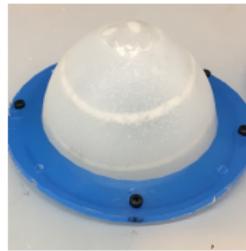
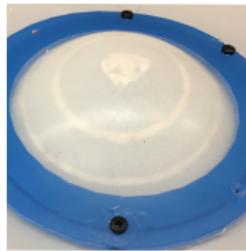
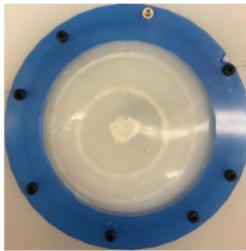
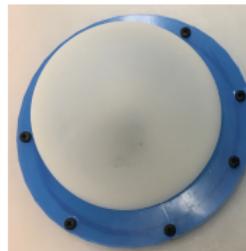
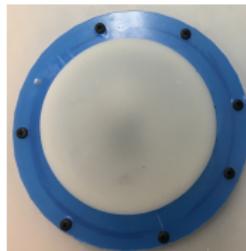
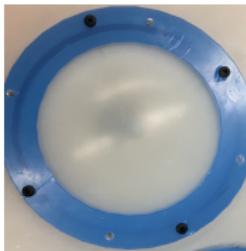
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Problem Setup



# Tension/Compression Analysis

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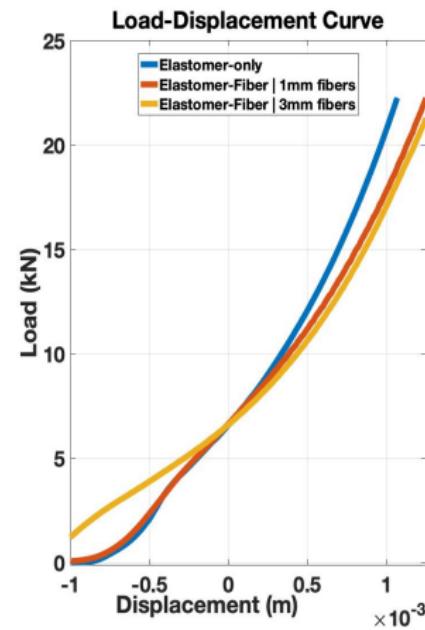
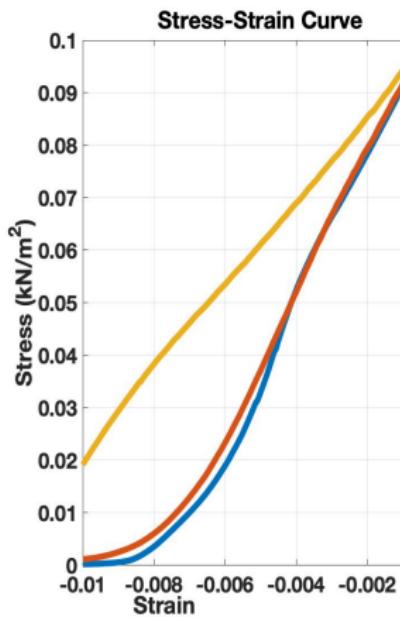
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# Head Motion Control (Independent Actuation)

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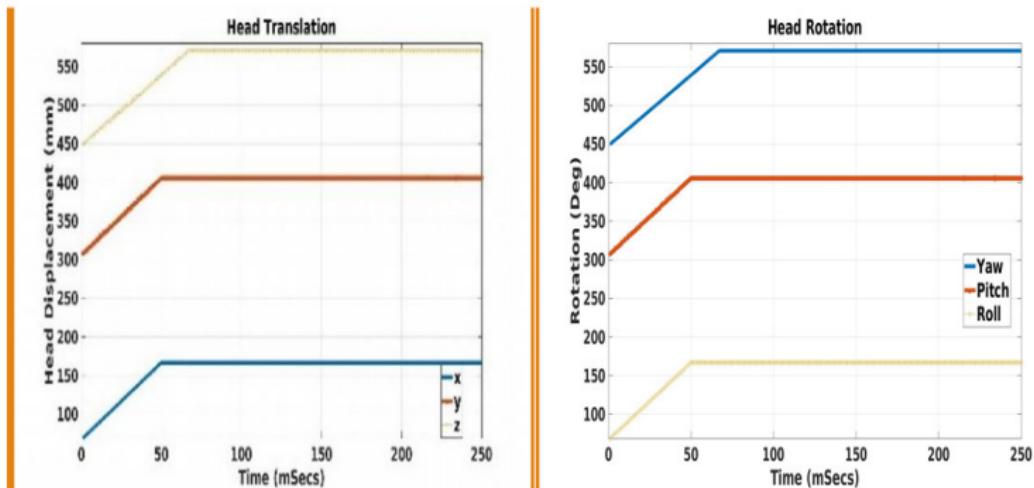
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Approach

Problem Setup



Head Translation along  $x, y, z$  for a task of raising the head by a certain threshold above the table

Head rotation in Euler angles for a task of tilting the head about the  $x, y, z$  axes on the treatment table.

# Ongoing/Future work

Treatment Planning in Radiation Therapy with AI and Soft Robots

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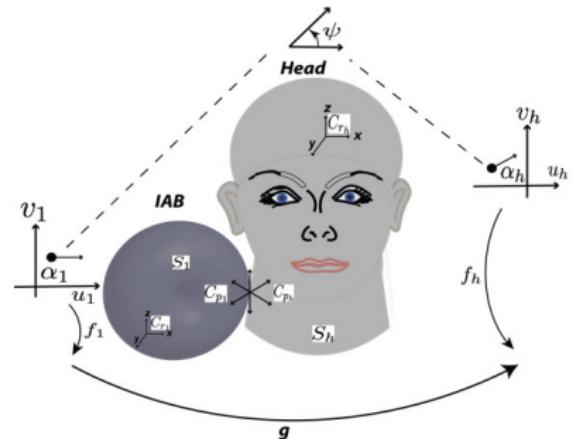
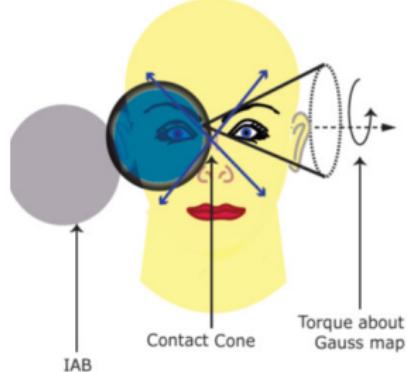
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Approach

Problem Setup

Continuum Mechanical Model Validation/Differential Geometry/Newton-Euler Dynamics



# Part II.B: Head Stabilization in Radiation Therapy (RT)

Treatment Planning in Radiation Therapy with AI and Soft Robots

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Approach

Problem Setup

- Head Stabilization in Cancer Radiation Therapy
  - Intensity-Modulated RT (IMRT): Earlier PhD Work

# Closed-Loop Motion Correction in IMRT

Treatment Planning in Radiation Therapy with AI and Soft Robots

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## Relevant Papers

- Ogunmolu, O., N. Gans, S. Jiang, and X. Gu. "SU-E-J-12: An Image-Guided Soft Robotic Patient Positioning System for Maskless Head-And-Neck Cancer Radiotherapy: A Proof-Of-Concept Study." *Medical Physics* 42, no. 6Part7 (2015): 3266-3266.
- Ogunmolu, Olalekan P., Xuejun Gu, Steve Jiang, and Nicholas R. Gans. "A real-time, soft robotic patient positioning system for maskless head-and-neck cancer radiotherapy: an initial investigation." In *2015 IEEE International Conference on Automation Science and Engineering (CASE)*, pp. 1539-1545. IEEE, 2015.
- Ogunmolu, Olalekan P., Xuejun Gu, Steve Jiang, and Nicholas R. Gans. "Vision-based control of a soft robot for maskless head and neck cancer radiotherapy," In *2016 IEEE International Conference on Automation Science and Engineering (CASE)*, pp. 180-187.IEEE, 2016.
- Ogunmolu, Olalekan, Adwait Kulkarni, Yonas Tadesse, Xuejun Gu, Steve Jiang, and Nicholas Gans. "Soft-neuroadapt: A 3-dof neuro-adaptive patient pose correction system for frameless and maskless cancer radiotherapy." In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 3661-3668. IEEE, 2017.
- Almubarak, Yara, Aniket Joshi, Olalekan Ogunmolu, Xuejun Gu, Steve Jiang, Nicholas Gans, and Yonas Tadesse. "Design and development of soft robot for head and neck cancer radiotherapy." In *Electroactive Polymer Actuators and Devices (EAPAD) XX*, vol. 10594, p. 1059418. International Society for Optics and Photonics, 2018.

# Simulation Testbed

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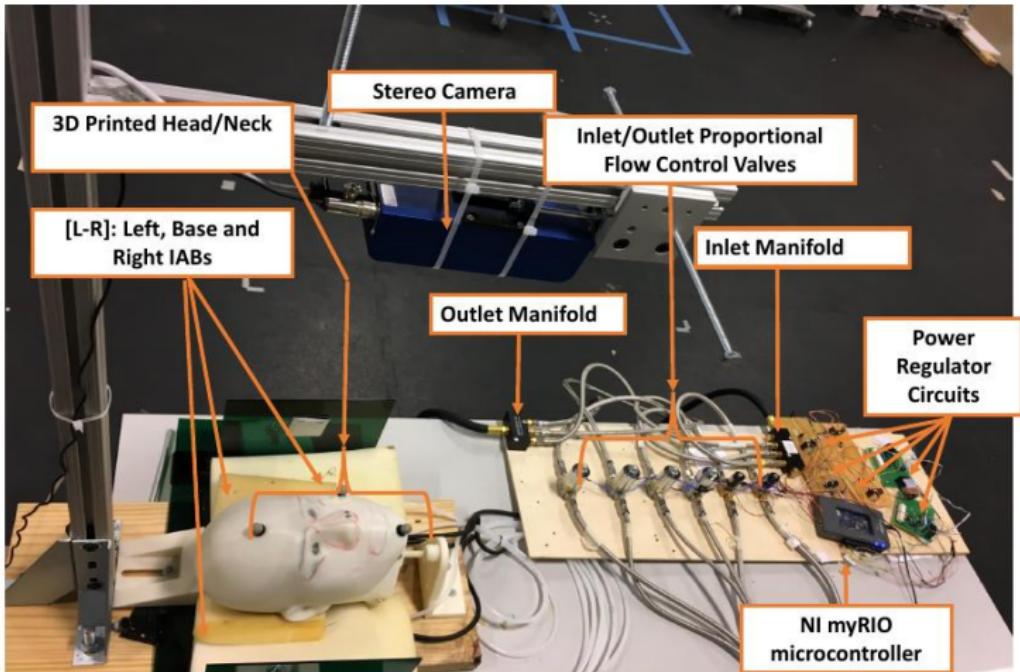
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## Hardware Description

# Control Proposals

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Approach

Problem Setup

- Solve a state feedback and feedforward regulation problem
- An adaptation model based on past states and controls:
  - $Z^N = \{u(k), u(k-1), \dots, u(k-n_u), y(k), \dots, y(k-n_y)\}$
- Design Goal:
  - Stabilize states,  $\mathbf{y} = [z, \theta, \phi]^T$
  - i.e. z, pitch, and roll.

# Model Reference Adaptive Control

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Approach

Problem Setup

- Model head and bladder dynamics
  - $\dot{\mathbf{y}} = \mathbf{A}\mathbf{y} + \mathbf{B}\Lambda(\mathbf{u} - f(\mathbf{y}, \mathbf{u})) + \mathbf{w}(k)$
  - $\mathbf{A}, \Lambda$  unknown,  $\mathbf{B}, \text{sgn}\Lambda$  known
- Approximate  $f(\mathbf{y}, \mathbf{u})$  by a neural network with continuous memory states
  - $\hat{f}(\mathbf{y}(k), \mathbf{u}(k-d))$  is realized with a *long-short term memory* cell (Horchreiter and Schmidhuber, '91, '97)
  - **purpose:** remember good adaptation gains

# Adaptive Neuro-Control Scheme

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Approach

Problem Setup

- Derive adaptive adjustment mechanism from Lyapunov analysis for Adaptive Control (Parks, P., 1966)

- $u = \underbrace{\hat{K}_y^T y}_{\text{state feedback}} + \underbrace{\hat{K}_r^T r}_{\text{optimal regulator}} + \underbrace{\hat{f}(y, u)}_{\text{approximator}}$

# Neural Network Model

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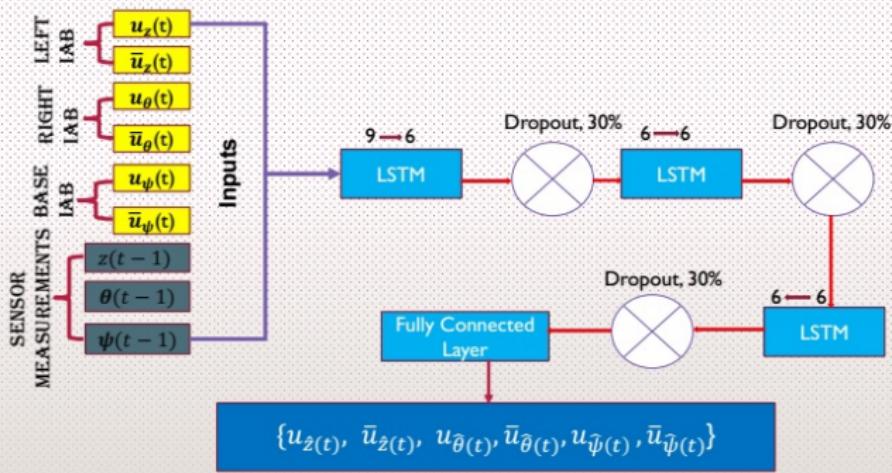
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## Neural Net Architecture



# Lyapunov Redesign: Theorem

- Given correct choice of adaptive gains  $\hat{\mathbf{K}}_y$  and  $\hat{\mathbf{K}}_r$ , the error state vector,  $\mathbf{e}(k)$  with closed loop time derivative  $\dot{\mathbf{e}}$ , is ***uniformly ultimately bounded***, and the state  $\mathbf{y}$  will converge to a neighborhood of  $\mathbf{r}$ .
- Choose a Lyapunov function candidate  $\mathbf{V}$  in terms of the generalized error state space  $\mathbf{e}$ , gains,  $\tilde{\mathbf{K}}_y^T$ ,  $\tilde{\mathbf{K}}_r^T$ , and parameter error  $\varepsilon_f(\mathbf{y}(k))$  space

$$\mathbf{V}(\mathbf{e}, \tilde{\mathbf{K}}_y, \tilde{\mathbf{K}}_r^T) = \mathbf{e}^T \mathbf{P} \mathbf{e} + \text{tr}(\tilde{\mathbf{K}}_y^T \Gamma_y^{-1} \tilde{\mathbf{K}}_y^T | \Lambda |) + \text{tr}(\tilde{\mathbf{K}}_r^T \Gamma_r^{-1} \tilde{\mathbf{K}}_r^T | \Lambda |)$$

# Stability Results

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See Proof in *Ogunmolu et al. IROS 2018*. In the end, we have

$$\begin{aligned}\dot{\mathbf{V}}(\cdot) &= -\mathbf{e}^T \mathbf{Q} \mathbf{e} - 2\mathbf{e}^T \mathbf{P} \mathbf{B} \boldsymbol{\Lambda} \boldsymbol{\varepsilon}_f \\ &\leq -\lambda_{low} \|\mathbf{e}\|^2 + 2\|\mathbf{e}\| \|\mathbf{P} \mathbf{B}\| \lambda_{high}(\boldsymbol{\Lambda}) \boldsymbol{\varepsilon}_{max}\end{aligned}$$

- $\lambda_{low}, \lambda_{high} \equiv$  minimum and maximum eigenvalues of  $\mathbf{Q}$  and  $\boldsymbol{\Lambda}$  respectively.
- $\dot{\mathbf{V}}(\cdot)$  is thus negative definite outside the compact set
- $\chi = \left( \mathbf{e} : \|\mathbf{e}\| \leq \frac{2\|\mathbf{P} \mathbf{B}\| \lambda_{high}(\boldsymbol{\Lambda}) \boldsymbol{\varepsilon}_{max}(\mathbf{y})}{\lambda_{low}(\mathbf{Q})} \right)$ 
  - i.e. the error  $\mathbf{e}$  is uniformly ultimately bounded, or  $\mathbf{y}(t) \rightarrow 0$  as  $t \rightarrow \infty$ .

# Results

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- Solving the general form of the Lyapunov equation, we have

$$\mathbf{P} = \begin{bmatrix} -\frac{170500}{2668} & 0 & 0 \\ 0 & -\frac{170500}{2668} & 0 \\ 0 & 0 & -\frac{170500}{2668} \end{bmatrix}$$

- Solenoid valves operate in pairs

- set

$$\mathbf{B} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

- $\mathbf{B}$  maps to the 3-axes controllers

$$[u_z \quad u_\theta \quad u_\psi]^T$$

- non-zero terms are the max. duty-cycle to valves

# Results: Z and Pitch Motions

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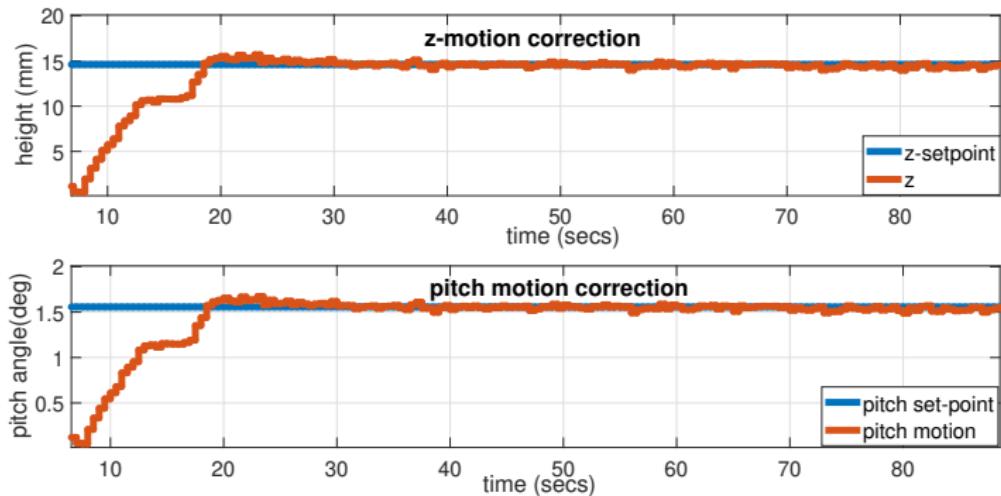
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Goal command:  $(z, \theta, \phi) = (2.5\text{mm}, 0.25^\circ, 35^\circ)$  to  $(14\text{mm}, 1.6^\circ, 45^\circ)^T$ .

# Results: Roll Motion

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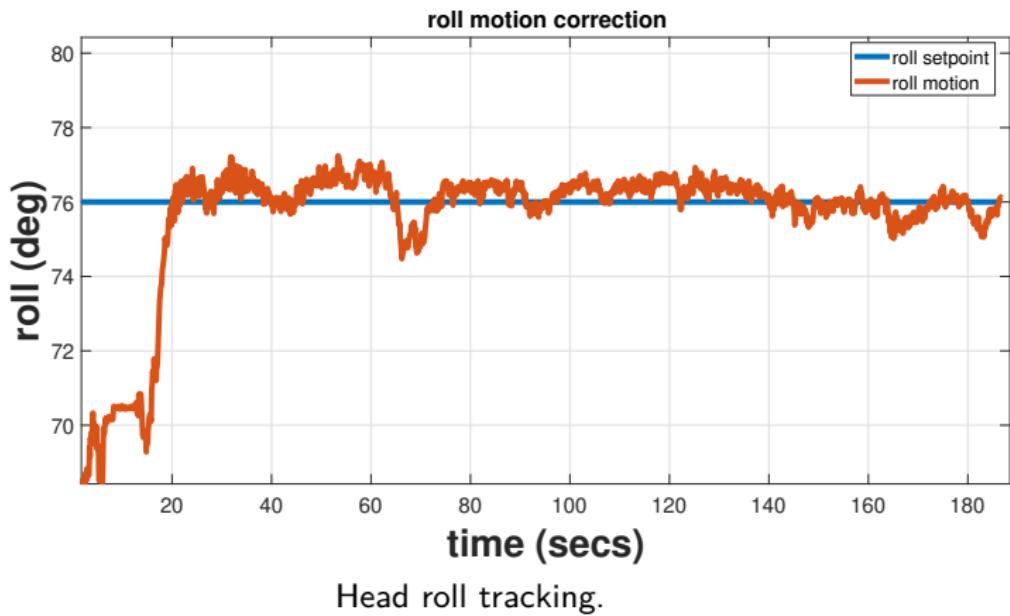
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# Part III: Robustness Margins and Robust Deep Policies

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- Robustness Margins and Robust Deep Policies for Nonlinear Control

# Iterative Dynamic Game

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## Relevant Papers

- Ogunmolu, Olalekan, Nicholas Gans, and Tyler Summers. "Minimax iterative dynamic game: Application to nonlinear robot control tasks." In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 6919-6925. IEEE, 2018.
- Ogunmolu, Olalekan, Nicholas Gans, and Tyler Summers. "Robust zero-sum deep reinforcement learning." *arXiv preprint arXiv:1710.00491* (2017).
- Summers, Tyler, Olalekan Ogunmolu, Nicholas Gans. "Robustness Margins and Robust Guided Policy Search for Deep Reinforcement Learning." In *IEEE/RSJ International Conference on Robots and Intelligent Systems,(Abstract Only Track)*, vol. 8. 2017.

# The robustness conundrum

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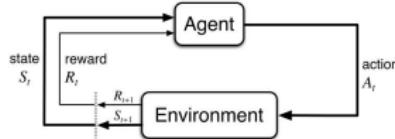
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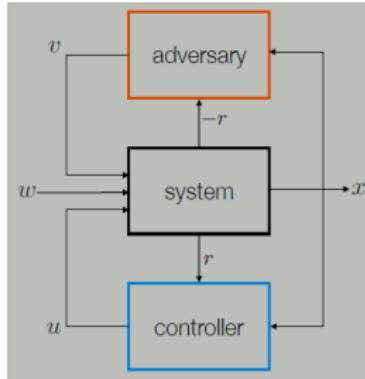
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Problem Setup

- How to know *a priori* a policy's robustness limits?



- How to inculcate robustness into multistage decision policies?



# Problem Setup

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- To quantify the brittleness, we optimize the stage cost

$$\max_{\mathbf{v}_t \sim \psi \in \Psi} \left[ \sum_{t=0}^T \underbrace{c(\mathbf{x}_t, \mathbf{u}_t)}_{\text{nominal}} - \gamma \underbrace{g(\mathbf{v}_t)}_{\text{adversarial}} \right]$$

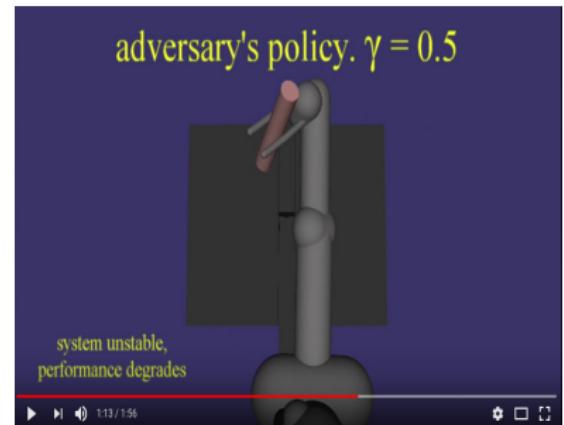
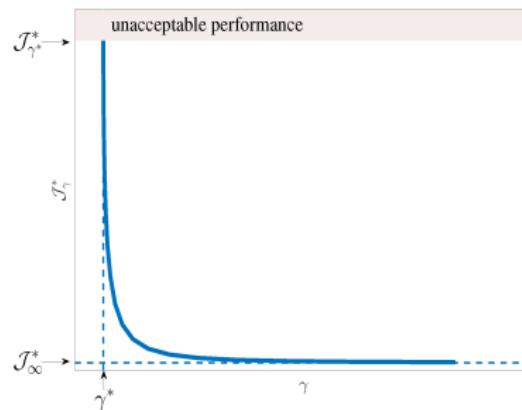
- To mitigate lack of robustness, we optimize the *cost-to-go*

$$\mathcal{J}_t(\mathbf{x}_t, \pi, \psi) = \min_{\mathbf{u}_t \sim \pi} \max_{\mathbf{v}_t \sim \psi} \left( \sum_{t=0}^{T-1} \ell_t(\mathbf{x}_t, \mathbf{u}_t, \mathbf{v}_t) + L_T(\mathbf{x}_T) \right),$$

- and seek a saddle point equilibrium policy that satisfies

$$\mathcal{J}_t(\mathbf{x}_t, \pi^*, \psi) \leq \mathcal{J}_t(\mathbf{x}_t, \pi^*, \psi^*) \leq \mathcal{J}_t(\mathbf{x}_t, \pi, \psi^*),$$

# Results: Brittleness Quantification



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# Results: Iterative Dynamic Game

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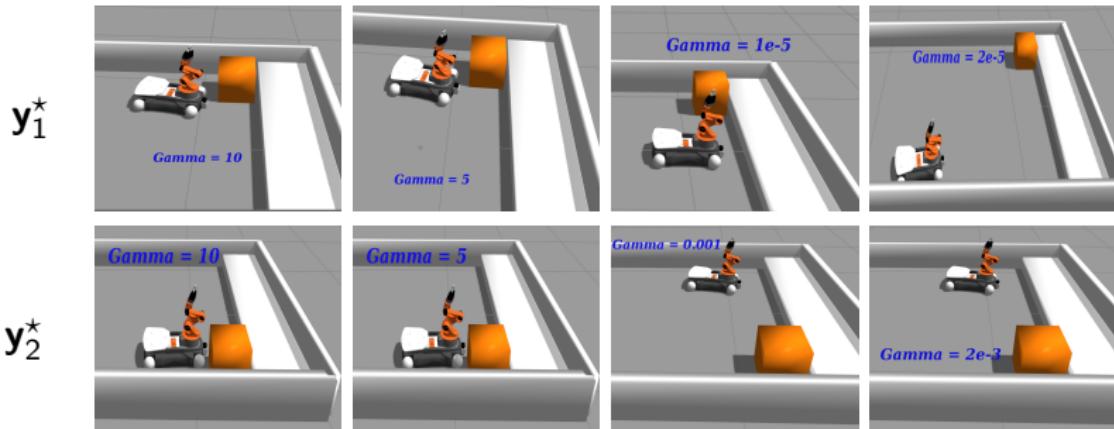


Table: \*

End pose of the KUKA platform with our iDG formulation given different goal states and  $\gamma$ -values

# End of Slides

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**Thank you!**

# Future Work: MRI/RT Immobilization

- Explore multiple parallel robot mechanisms for head motion correction
- Adopt best practices from one of the SOTA modeling approaches viz
  - *constant curvature approach* [Godage et al. (2016)],
  - the *continuous Cosserat approach* [Renda et al. (2014)], and
  - the *multi-body hyper-redundant model* [Kang et al. (2012)].

# Future Work

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Problem Setup

- Robust Stabilization via inverse optimality
  - Imbibing robust Lyapunov stability into deep optimal controllers
    - Build on Freeman and Kokotovic's point-wise min-norm robust control lyapunov function to realize a meaningful value function (Int. Journal of Optimal Control, 1996)
    - Simplify algorithm for real-time control
  - Carry out numerical and experimental verification and validation
  - Important in multistage decision policies, reinforcement learning controllers

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- Johannes Heinrich, Marc Lanctot, and David Silver. Fictitious self-play in extensive-form games. In *International Conference on Machine Learning*, pages 805–813, 2015.
- Radhini Chelvarajah, Brigid Leighton, Linda Martin, Wayne Smith, and Rachael Beldham-Collins. Cranial immobilisation—is there a better way? *Radiographer*, 51(1):29–33, 2004.
- Andrew Belcher. *Patient Motion Management with 6-DOF Robotics for Frameless and Maskless Stereotactic Radiosurgery*. PhD thesis, The University of Chicago, 2017.
- Olalekan Ogunmolu and Rodney Wiersma. A Real-Time Patient Head Motion Correction Mechanism for MRI-Linac Systems. In *Joint AAPM / COMP Meeting, Virtual*, 2020.
- Isuru S Godage, Gustavo A Medrano-Cerda, David T Branson, Emanuele Guglielmino, and Darwin G Caldwell. Dynamics for variable length multisection continuum arms. *The International Journal of Robotics Research*, 35(6):695–722, 2016.
- Federico Renda, Michele Giorelli, Marcello Calisti, Matteo Cianchetti, and Cecilia Laschi. Dynamic model of a multibending soft robot arm driven by cables. *IEEE Transactions on Robotics*, 30(5):1109–1122, 2014.
- Rongjie Kang, David T Branson, Emanuele Guglielmino, and Darwin G Caldwell. Dynamic modeling and control of an octopus inspired multiple continuum arm robot. *Computers & Mathematics with Applications*, 64(5):1004–1016, 2012.