Automating Treatment Planning in Radiation Therapy

Olalekan Ogunmolu

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BOO Workflow
Innovation

Head Stabilization
Background – LINACs RT
MRI-LINACs
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iDG
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Presented by **Lekan Molu** (`Lay-con Moh-lu`)

March 10, 2021

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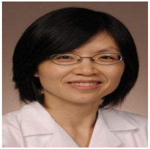
Acknowledgments

Steve Jiang, UTSW

Nick Gans, UTARI

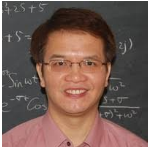
Xuejun Gu, UTSW



Dan Nguyen, UTSW

Rod Wiersma, Penn

Xinmin Liu, Penn



Tyler Summers, UTD

Yonas Tadesse, UTD

Funding Sources

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NIH NATIONAL CANCER INSTITUTE

CANCER PREVENTION & RESEARCH INSTITUTE OF TEXAS

Talk Outline

- 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 (RT)
  - Intensity-Modulated RT (IMRT): Earlier PhD Work
  - Magnetic Resonance Imaging and Linear Accelerator Systems (MRI-LINACs)
- Robustness Margins and Robust Deep Policies for Nonlinear Control

Research Significance

2021 → 1,898,160 U.S. cancer cases[1] → 608,570 deaths → $246 billion in costs by 2030[1]

Cancer Treatment

- Chemotherapy/Radiosurgery.
- Radiation Therapy (RT).

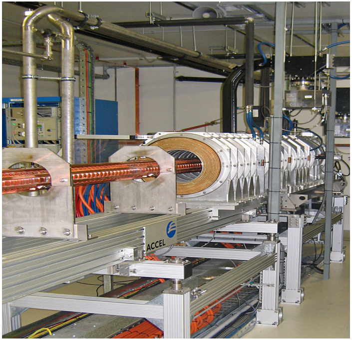
RT Signif.

- Approx. 40% of all curative cancer treatment modality are performed with RT[1].
- Cost-effective -- accounting for only 5% of the total cost of cancer care[3].

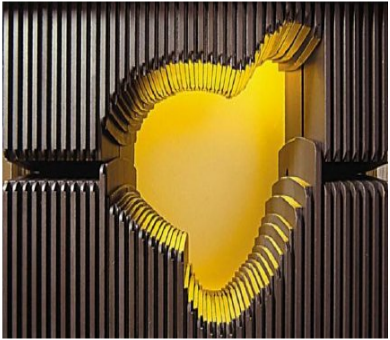
Imaging

- CT images in RT = Low soft tissues contrast ⇒ OARs toxicity during treatment planning.
- MRI of brain, and head and neck (H&N) cancers provides exceptional soft tissues contrast and allows greater delineation of cancerous from non-cancerous tissues.

IMRT Treatment Planning (Beam Delivery)



The Australian Synchrotron.



A Multi-leaf collimator, ©Varian.

Radiation Delivery Couch and Gantry

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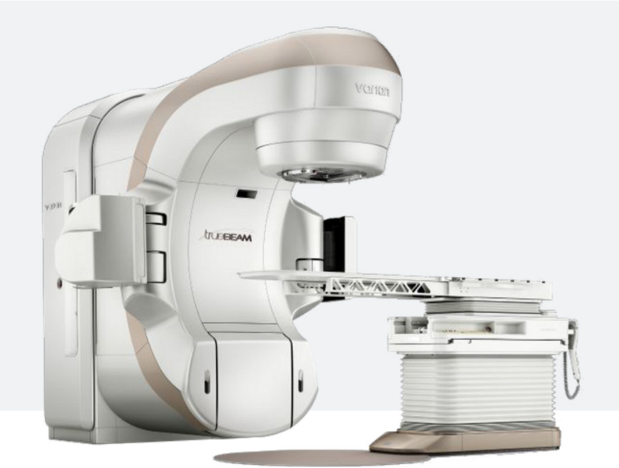

Varian's TrueBeam Radiotherapy System.

Part I.A: Beam Orientation Optimization (BOO)

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- Beam Orientation Optimization (BOO)
  - Monte Carlo Tree Search and Neuro-Dynamic Programming

Contributions

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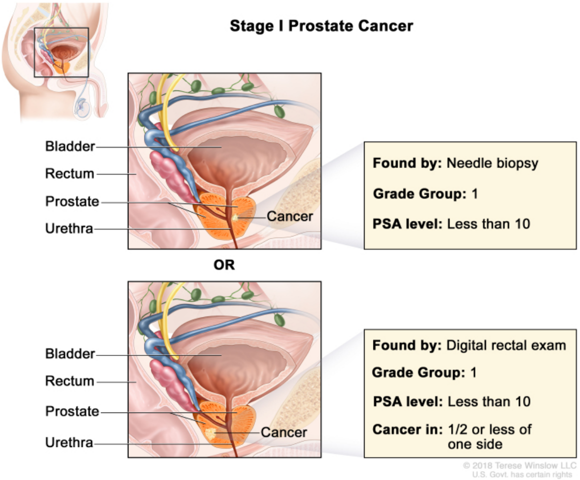
Relevant Publications

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.

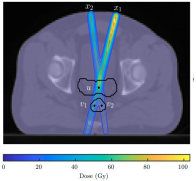
- A sparse tree lookout strategy for games with large state spaces guides transition between beam angle sets
- Tree lookout strategy guided by a deep neural network policy

Protate Cancer Example

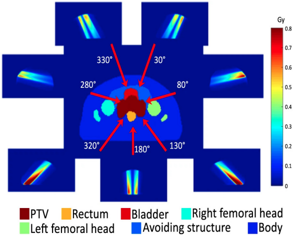


BOO Process: Fluence Map Optimization

Prostate CT slice



Prostate before BOO



Fluence Map

BOO Workflow

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Manually Selection/Protocols Adoption

Laborious process; could take up to 5 days for head and neck cancer treatment.

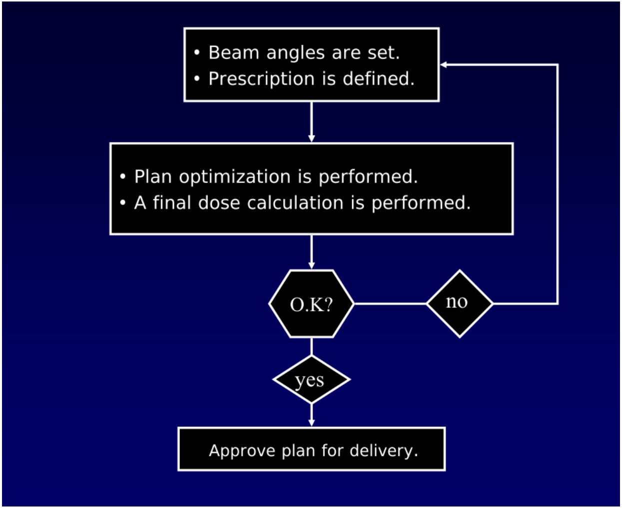
Pre-solve Large Sparse Dose Influence Matrix

Takes hours to solve for a single patient. Days/months for multiple patients.

Solve Fluence Map Optimization

Time-consuming: Often takes minutes.

Treatment Plan Flowchart



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

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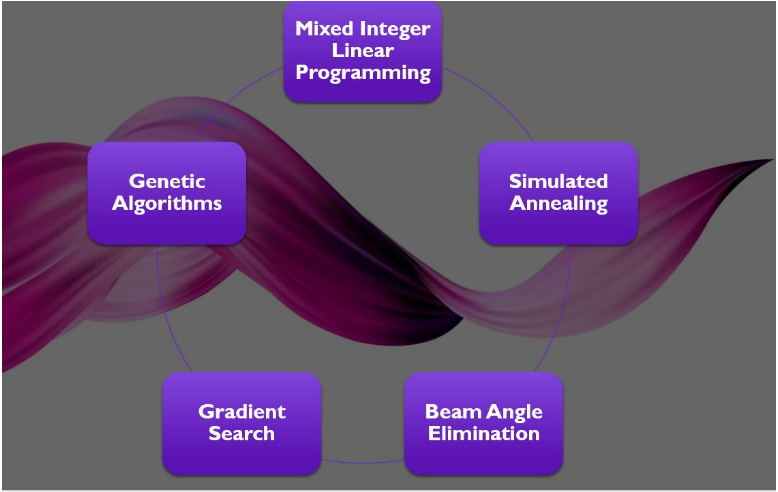
Current Approaches and Limitations



Innovation

- A Tower Neural 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.

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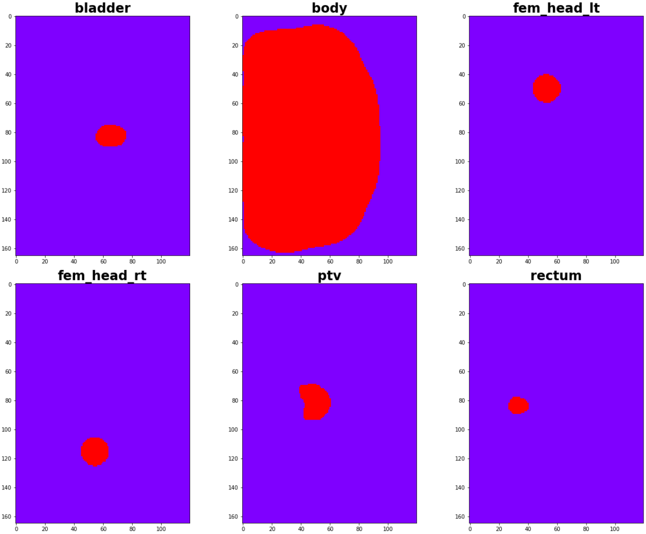
State Encoding: Prostate Organ Masks



State Representation: Beam Angles

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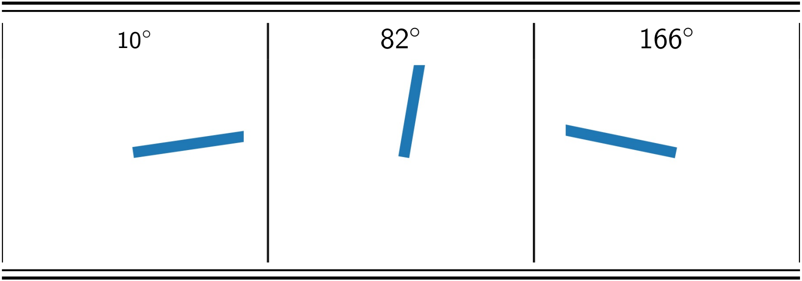

State Representation

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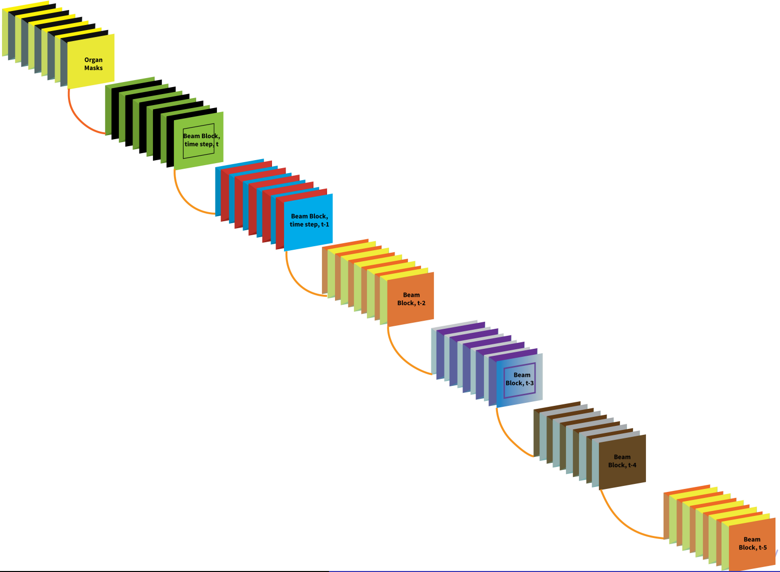
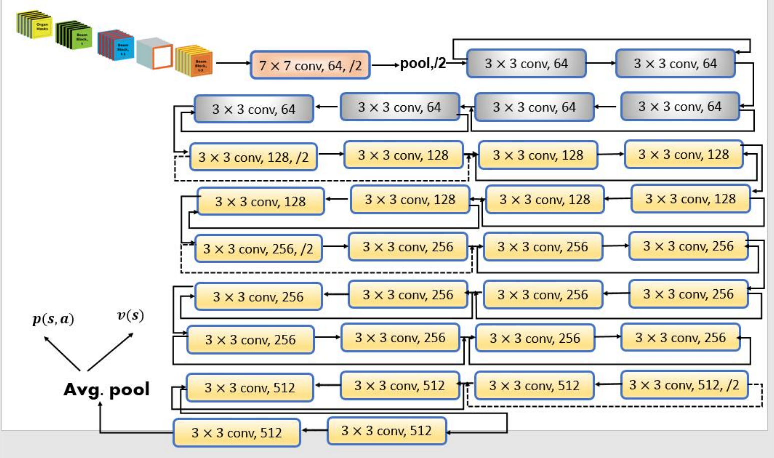
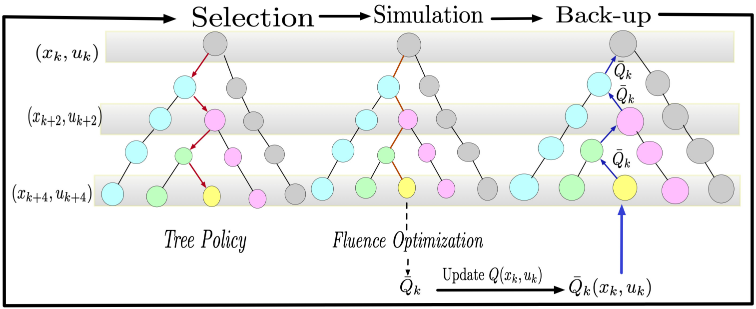


Two-player Fictitious network play with ResNet



Tree Representation and Game Simulation



Tree Composition

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Every **node** of the tree, $\boldsymbol{x}$, has the following fields:

- a pointer to the parent that led to it, $\boldsymbol{x}.p$;
- the beamlets, $\boldsymbol{x}_b$, stored at that node; $b = \{1, \ldots, m\}$;
- a set of move probabilities prior, $p(s, a)$;
- a pointer $\boldsymbol{x}.\boldsymbol{r}$, to the reward r_t, for the state $\boldsymbol{x}_t$;
- 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 $\boldsymbol{x}.child_i$ to each of its children nodes.

Saddle Point Strategy Formulation

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- **Saddle point strategies** for optimal control sequence pair $\{a_t^{p_1^*}, a_t^{p_2^*}\}$ recursively obtained by optimizing, $V_t(s, a)$

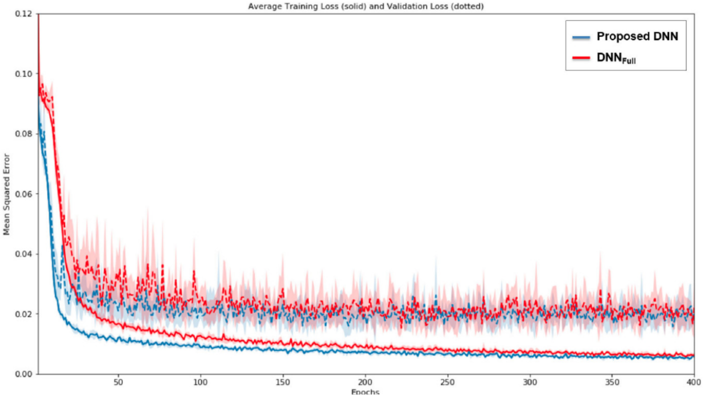
$$V_t^*(s) = Q_t^*(s_t, \pi_t^{p_1}, \pi_t^{p_2}) = \min_{\pi^{p_1} \in \Pi^{p_1}} \max_{\pi^{p_2} \in \Pi^{p_2}} Q_t^\star(s_t, \pi^{p_1}, \pi^{p_2})$$
$$\forall s_t \in \mathcal{S}, \pi^{p_1} \in \Pi^{p_1}, \pi^{p_2} \in \Pi^{p_2}.$$

such that

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

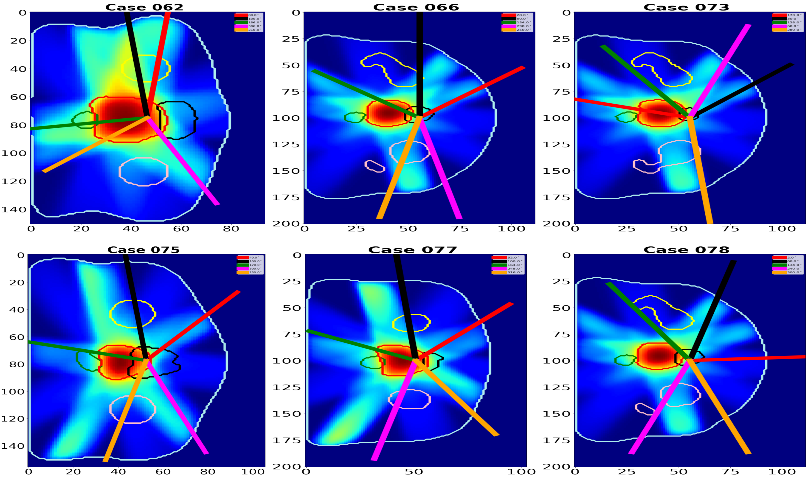
- p_1, p_2 respectively generating a **mixed strategy** via **averaging the outcome** of individual plays.

Training and Validation Loss

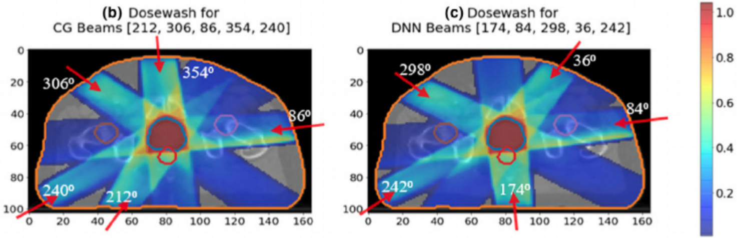


Average training (solid) and validation (dotted) loss function (MSE) values across six cross-validation folds for the network (blue) and full network.

BOO Results: Testing of self-play network



Column Generation vs Neural Network



Dose-Volume Histogram of CG vs DNN architectures [Sadeghnejad Barkousaraie, Azar and Ogunmolu, Olalekan and Jiang, Steve and Nguyen, Dan (2019)].

Conclusions

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- Deep Neural Network optimizes network weights in a separate multiprocessing thread; Network outputs probabilities used to guide search;
- Sparse lookahead search builds tree with nodes labeled by state-action pairs in an alternating manner; sample rewards stored on edges connecting state-action with state nodes;
- Beam angles prediction takes between 2-3 minutes with MCTS vs. ~ 60 seconds with Column Generation Pre-training.

Head Stabilization in Radiation Therapy (RT)

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- Head Stabilization in Cancer Radiation Therapy
  - Intensity-Modulated RT (IMRT)

Robotic Radiosurgery

Penn
UNIVERSITY *of* PENNSYLVANIA

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

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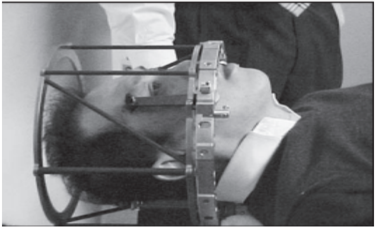
DEPARTMENT OF RADIATION ONCOLOGY, PENN SCHOOL OF MEDICINE

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

Correcting Head Motion: RT and MRI-LINACs

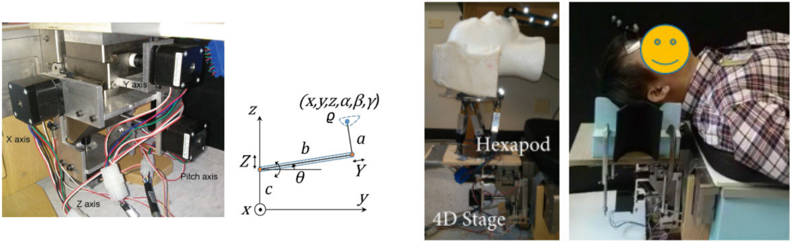


(a) The BRW SRS Frame [Chelvarajah et al. (2004)]

(b) Thermoplastic masks

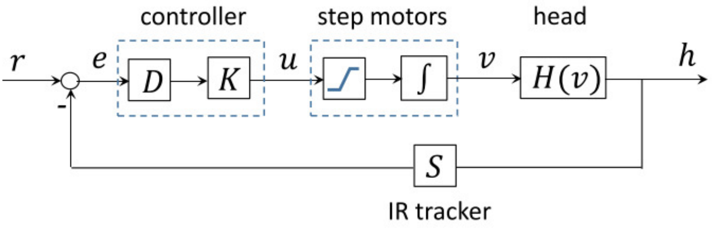
(c) Frame With MRI Coils (PSOM)

4-D Motion Correction Stage



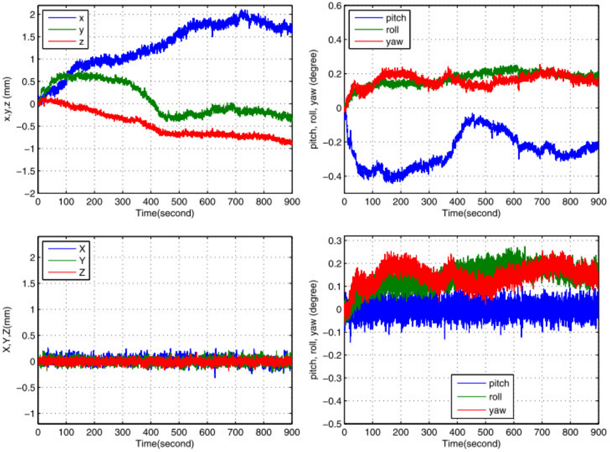
Liu et al. (2015)

4-DOF Motion Controller Block Diagram



Liu et al. (2015)

Phantom Feedback Motion Correction Results



Time response of feedback control without (left) and with (right) decoupling control [Liu et al. (2015)].

Human Volunteer Feedback Motion Correction Results

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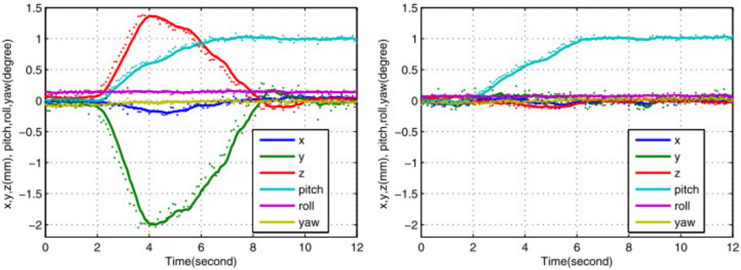

Head Motion Without and With Motion Correction. Left: Coupled Axes; Right: Decoupled Axes.

SRS: Wiersma Stewart-Gough Platform

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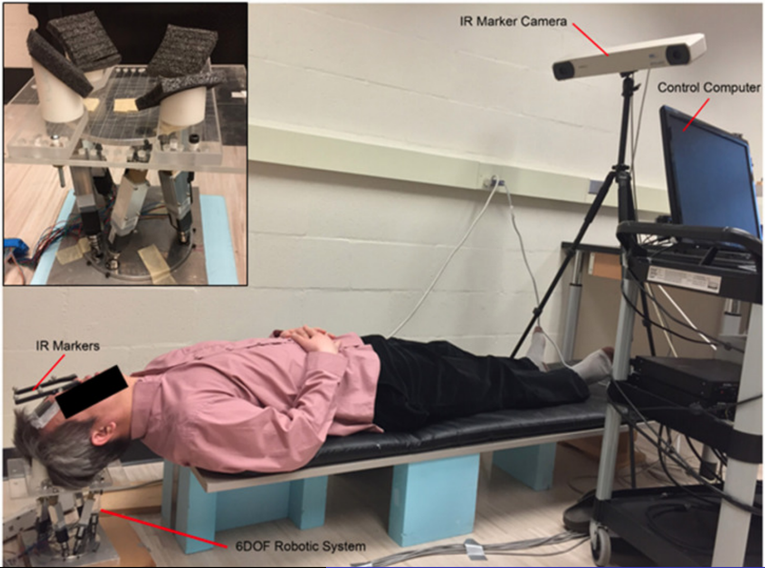
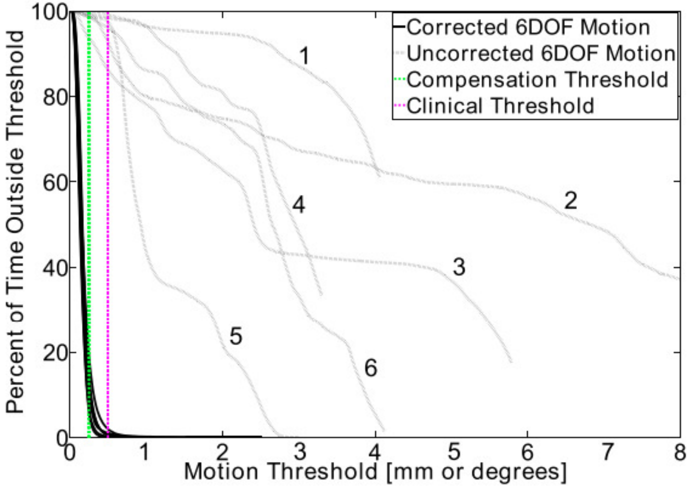


6-DOF Motion Correction Results



Drawbacks of current solutions

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- Rigid patient's body assumption
- Non-compliant immobilization devices
- Invasiveness during radiosurgery/RT
- Attenuation of photon beams

Radiation Delivery Couch and Gantry

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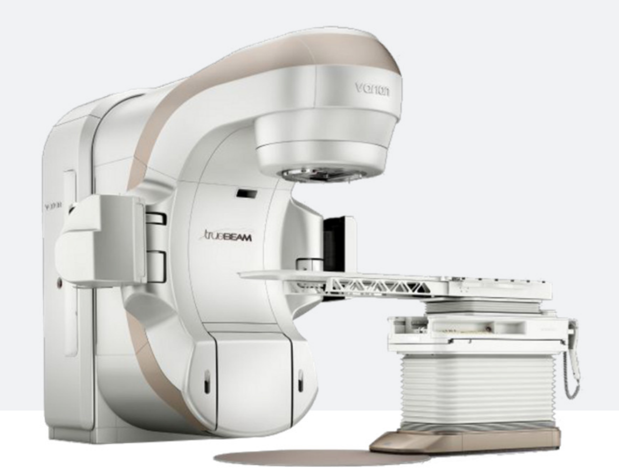
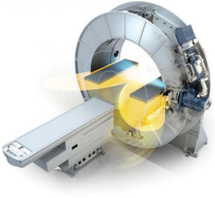


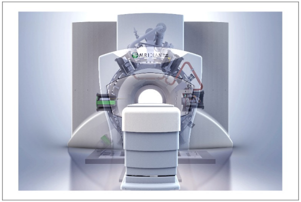
Varian's TrueBeam Radiotherapy System.

Next-Gen RT Treatment with MRI-LINACs

Elekta AB's (Sweden)

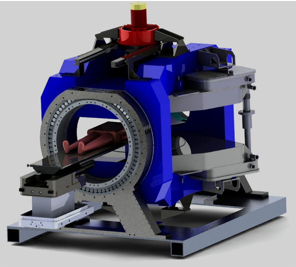


ViewRay's MRIdian



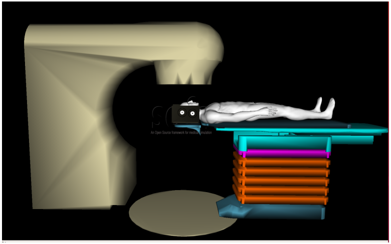
Elekta AB's (Sweden)

MagnetΓx (Canada) Aurora RT

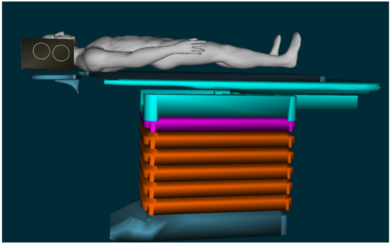


Soft Robots for Head Motion Compensation

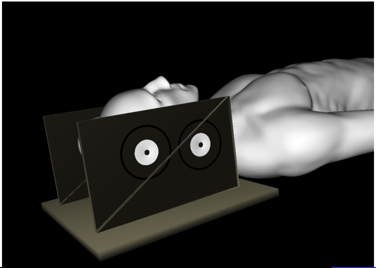
IMRT Setup



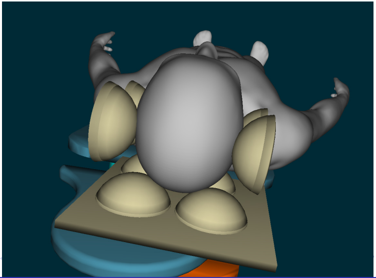
IMRT/MRI



Head and Robot Panel



Head-Robot Closeup



Morphing in Cephalopods

Morph Stage 1

Morph Stage 2

Morph Stage 3

Morph Stage 4

Morph Stage 5

Morph Reversal

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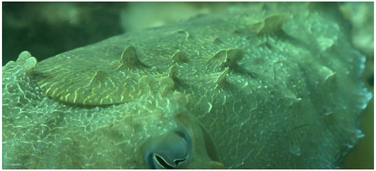
Cephalopods Neural-Controlled Physical Texture

Raises Periscope



Papillae

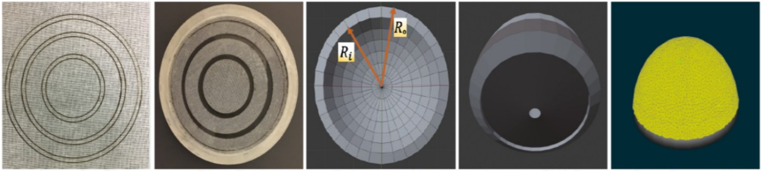
Papillae Up

Papillae $\times$ Papillae

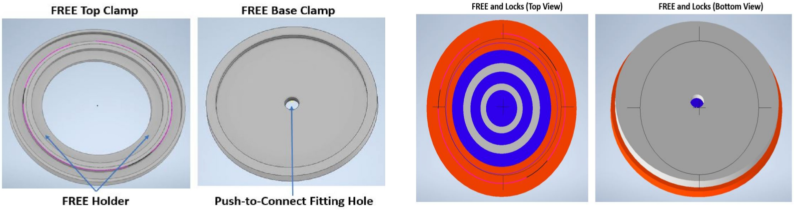
Cuttlefish' Morphin ©Roger Hanlon, YouTube.

Cephalopods-inspired Actuator Design

Circumferentially Constrained And Radially Symmetric Elastomers (CCOARSE).



(a) Laser-Cut Fiber (b) Fiber+Rubber (c) Deformation Model (d) Actuator+PVC Base (e) Finite Element Model



(f,g) (h)

[Pikul et al. (2019)]

Nonlinear Elastic Deformation Analysis

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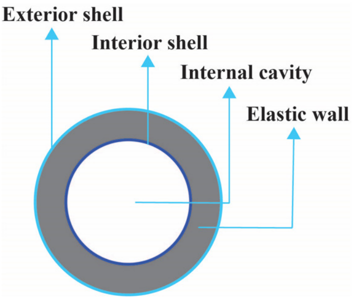
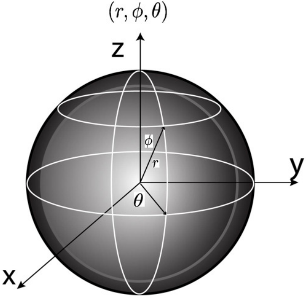
IAB SHELLS AND AIR CAVITY/DEFORMATION ANALYSIS





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

Soft IK via Boundary Value Problem

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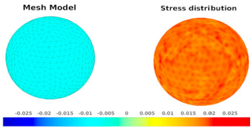
- With Cauchy's laws of motion, solve boundary volume problem of traction, and find that

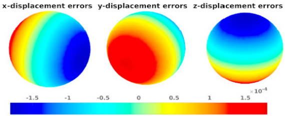
$$P(r) = \int_{r_i}^{r_0} \left[2C_1 \left(\frac{r}{R^2} - \frac{R^4}{r^5} \right) + 2C_2 \left(\frac{r^3}{R^4} - \frac{R^2}{r^3} \right) \right] dr \qquad (1)$$

- *i.e.* Given a prescribed radius, find pressure to deform actuator between configurations

Volumetric Deformation Results (Simulation)



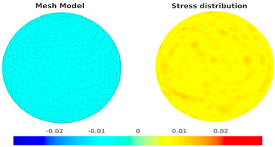
(a) **Left**: Mesh model. **Right**: Stress distribution on outer skin.



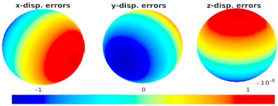
(b) Displacement errors along x, y, z coordinates.

Inputs					Outputs		
C_1	C_2	R_i	r_i	$R_\circ$	$r_\circ$	P	ΔV
$1.1e4$	$2.2e4$	.027	.03	.03	.033	.76	≈ 0

Fig. 6: Volumetric Deformation (Expansion).



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

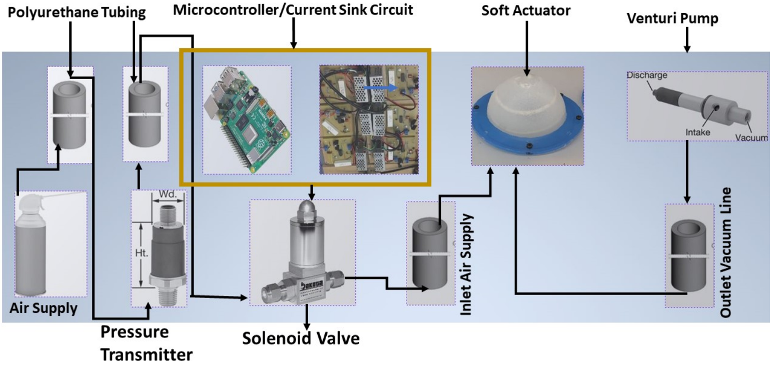


(b) Displacement errors along x, y, z coordinates.

Inputs					Outputs		
C_1	C_2	R_i	r_i	$R_\circ$	$r_\circ$	P	ΔV
$1.1e4$	$2.2e4$	.025	.03	.03	.028	$-.34$	≈ 0

Fig. 7: Volumetric Deformation (Compression).

Pneumatic Control and Deformation Scheme



Volumetric Deformation Results (Actual)

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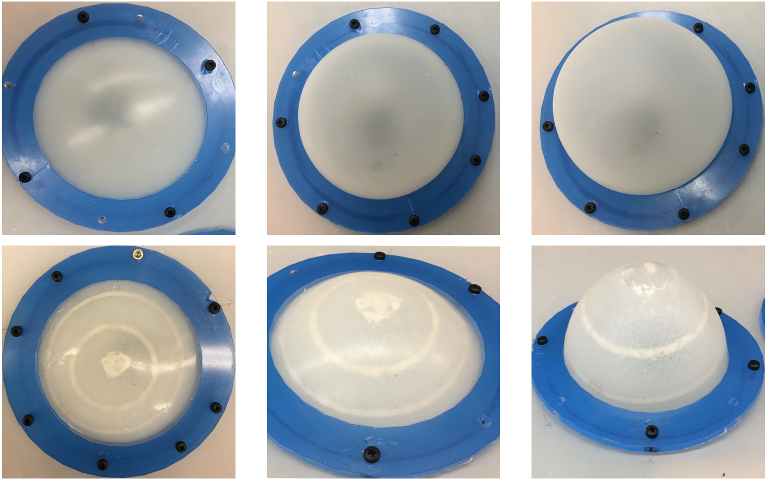
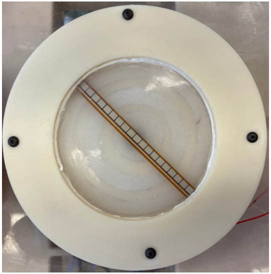
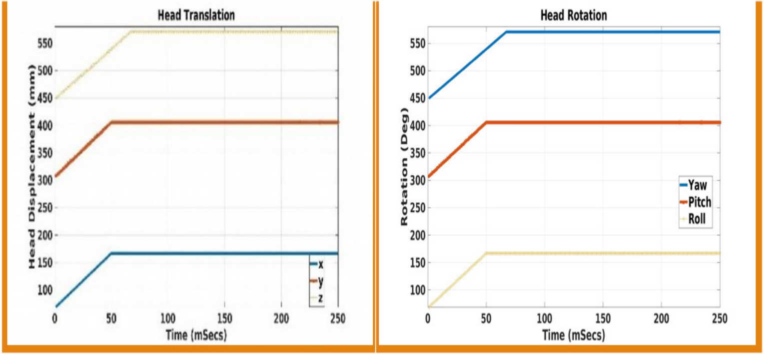


Actuator and Overall Mechanism with Phantom



Head Motion Open Loop Control

Independent Actuation

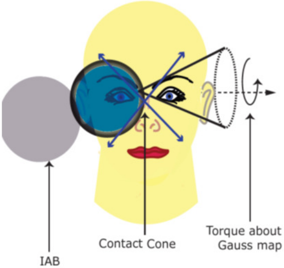


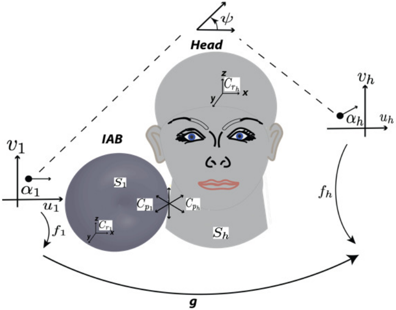
Head Translation along x, y, z for a task of raising the head by a certain threshold above the table

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

Ongoing Work: 6-DOF Closed-loop Control

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





3-DOF Simulation Testbed

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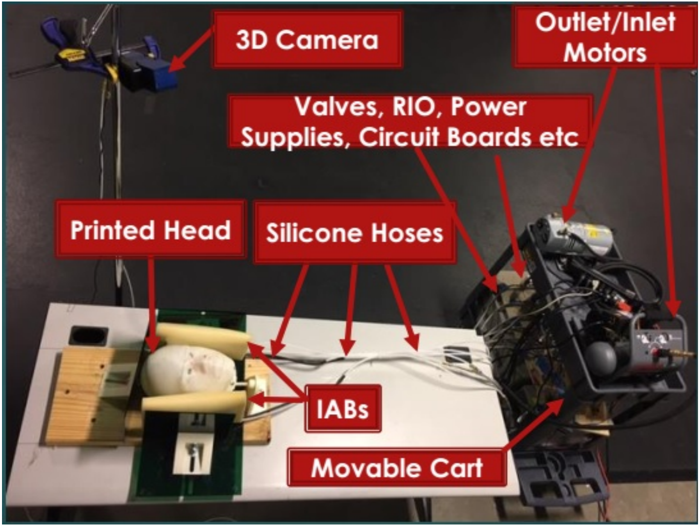

3-DOF Model Reference Adaptive Control

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Future Work

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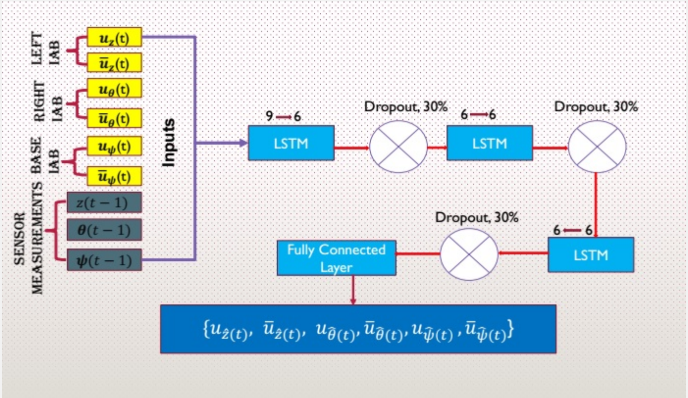
- Model head and bladder dynamics as
  - $\dot{\boldsymbol{x}} = \mathbf{A}\boldsymbol{x} + \mathbf{B}\boldsymbol{\Lambda}\left(\mathbf{u} - f(\boldsymbol{x}, \mathbf{u})\right) + \mathbf{w}(k)$
- Approximate $f(\boldsymbol{x}, \mathbf{u})$ by a neural network with continuous memory states
- Derive adaptive adjustment mechanism from Lyapunov analysis for Adaptive Control Parks (1966)
- $\mathbf{u} = \underbrace{\hat{\mathbf{K}}_x^{\mathbf{T}}\boldsymbol{x}}_{\text{state feedback}} + \underbrace{\hat{\mathbf{K}}_r^{\mathbf{T}}\mathbf{r}}_{\text{optimal regulator}} + \underbrace{\hat{f}(\boldsymbol{x}, \mathbf{u})}_{\text{approximator}}$

Neural Network Architecture

Neural Net Architecture

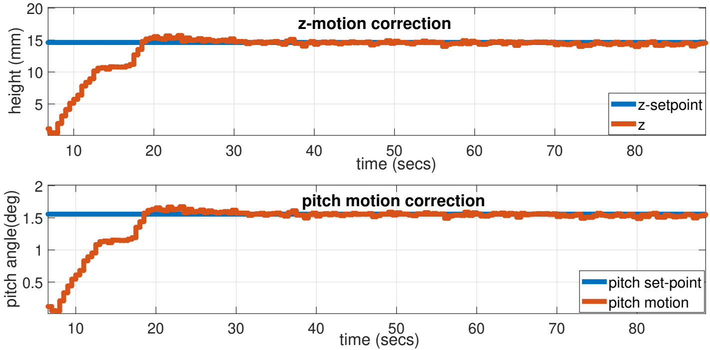


Lyapunov Redesign: Theorem

- For correct adaptive gains, $\hat{\mathbf{K}}_x$ and $\hat{\mathbf{K}}_r$, $\mathbf{e}(k)$ is ***uniformly ultimately bounded***, and the state $\boldsymbol{x}$ converges to a neighborhood of $\mathbf{r}$.
- Choose a $\mathbf{V}$ in terms of $\mathbf{e}$; $\tilde{\mathbf{K}}_x^T$, $\tilde{\mathbf{K}}_r^T$; and parameter error $\varepsilon_f(\boldsymbol{x}(k))$ space

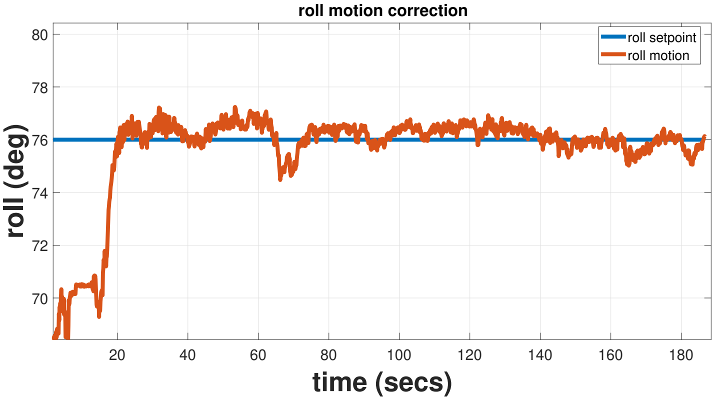
$$\mathbf{V}(\mathbf{e}, \tilde{\mathbf{K}}_x, \tilde{\mathbf{K}}_r^T) = \mathbf{e}^T\mathbf{P}\mathbf{e} + \mathbf{tr}(\tilde{\mathbf{K}}_x^T \boldsymbol{\Gamma}_x^{-1} \tilde{\mathbf{K}}_x^T |\boldsymbol{\Lambda}|) + \mathbf{tr}(\tilde{\mathbf{K}}_r^T \Gamma_r^{-1} \tilde{\mathbf{K}}_r |\boldsymbol{\Lambda}|)$$

Results: Z and Pitch Motions



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

Results: Roll Motion



Head roll tracking.

Conclusions

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Future Work

References

- Non-invasive soft robot for head motion compensation ✓
- Photons-transparent as opposed to rigid/electro-mechanical devices/robots ✓
- Adaptible under MRI coils for newer MRI-LINACs ✓

Part III: Robustness Margins and Robust Deep Policies

- Robustness Margins and Robust Deep Policies for Nonlinear Control

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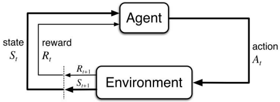
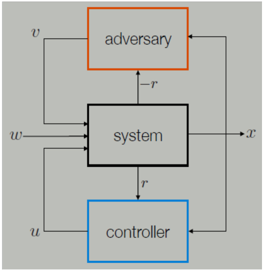
The robustness conundrum

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



- How to inculcate robustness into multistage decision policies?



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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*

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

- and seek a saddle point equilibrium policy that satisfies

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

Results: Brittleness Quantification

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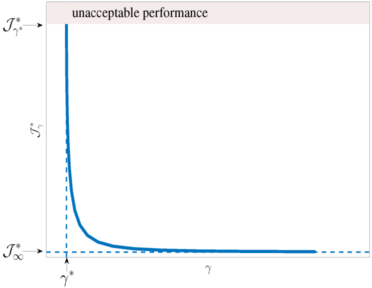
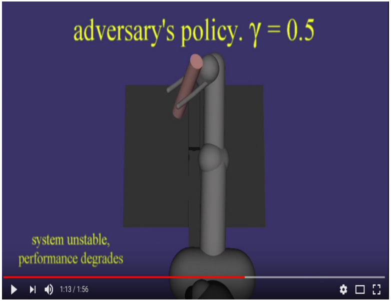
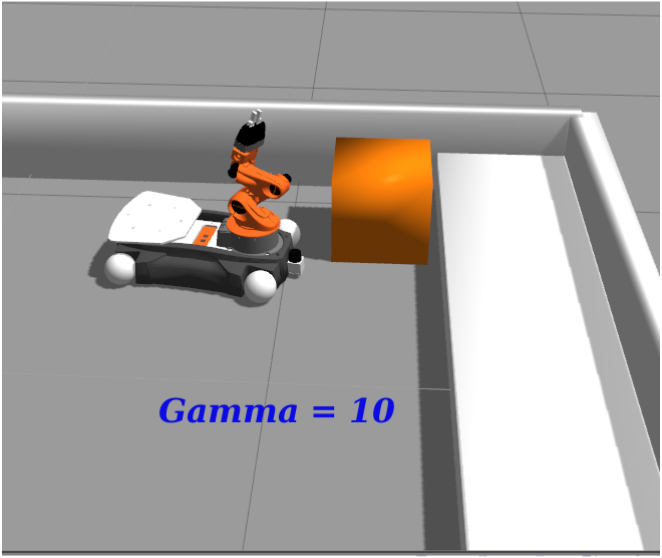




Results: Iterative Dynamic Game



Future Work: MRI/RT Immobilization

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Future Work

References

- Explore multiple parallel robot mechanisms for head motion correction.
- Adopt iterative dynamic game approach [Ogunmolu et al. (2018)] for solving robust controller for head stabilization.
- Build on Freeman and Kokotovic's point-wise min-norm robust control lyapunov function to realize a meaningful value function in deep policies [Freeman and Kokotovic (1996)].

Conclusions

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Future Work

References

- Designed a non-invasive soft robot for head motion compensation in IMRT/emerging MRI-LINACs ✓
- Photons-transparent; Adaptible under MRI coils for newer MRI-LINACs ✓
- Fast inference of beam orientations in treatment planning: Approx 60 secs beams prediction time✓
- Adapted H-∞ control methods for quantifying the brittleness of deep policies✓
- Devised a min-max-trained deep saddle policy for mitigating model mismatch, transfer errors, and policy sensitivity e.t.c. ✓

End of Slides/More Acknowledgments

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James Pikul, Asst. Prof. Penn

Kevin Turner, Prof. Penn

Audrey Sedal, Res. Asst. Prof. TTIC

Rachel Thompson, Student MIT

Ireti Akinola, PhD Student, Columbia

George Pappas, Prof. Penn

Jethro Tan, SW Eng. PFN Tokyo

MAIA Lab Members, UTSW

Publications

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References

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Olalekan Ogunmolu, 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 *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Vancouver, BC, CA*, pages 3661–3668. IEEE, 2017.

App A: 3-DOF Closed-loop Control

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Appendices

App A: 3DOF CL Control

App B: 1DOF

Kalman Filtering

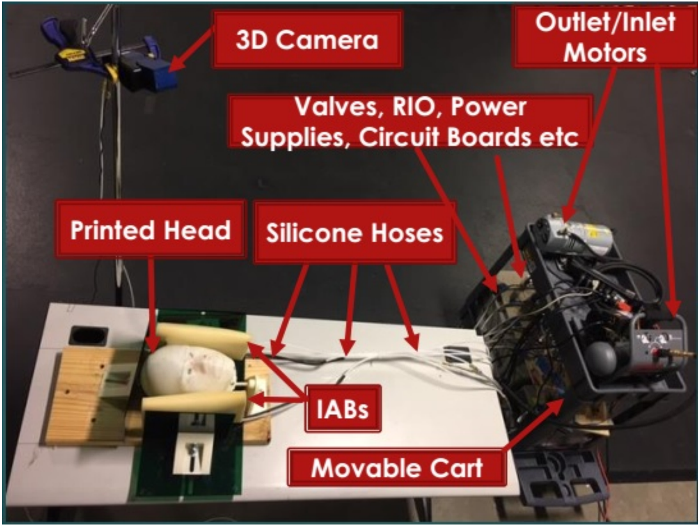
Sensor Fusion

System Identification

App C: CCOARSE Actuator

Closed-loop Phantom motion control along 3 DoFs with an adaptive neuro-controller.

3-DOF Simulation Testbed



Hardware Description

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Appendices

App A: 3DOF CL Control

App B: 1DOF

Kalman Filtering

Sensor Fusion

System Identification

App C: CCOARSE Actuator

Control Design Goals

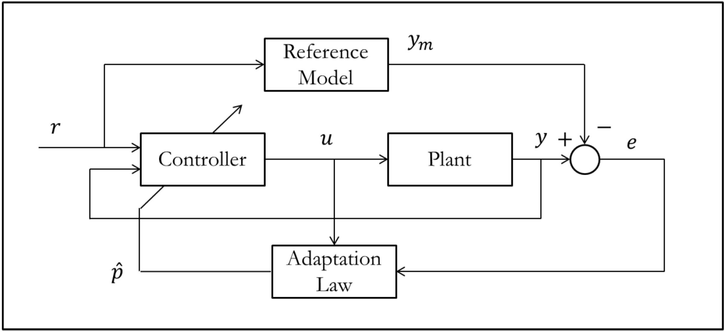
- Stabilize z, pitch, and roll states, *i.e.*

$$\boldsymbol{x} = \begin{pmatrix} z \\ \theta \\ \phi \end{pmatrix}$$

- By solving an adaptive state feedback controller, optimal regulation, and minimize parametric uncertainties

Control Design Goals

- Provide closed loop tracking given a desired trajectory, **r**
- Robustify system to (non-)parametric uncertainties



Indirect MRAC system. (Source mdpi.com)

Lyapunov Redesign: Theorem

- For correct adaptive gains, $\hat{\mathbf{K}}_x$ and $\hat{\mathbf{K}}_r$, $\mathbf{e}(k)$ is ***uniformly ultimately bounded***, and the state $\boldsymbol{x}$ converges to a neighborhood of $\mathbf{r}$.
- Choose a $\mathbf{V}$ in terms of $\mathbf{e}$; $\tilde{\mathbf{K}}_x^T$, $\tilde{\mathbf{K}}_r^T$; and parameter error $\varepsilon_f(\boldsymbol{x}(k))$ space

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

Stability proof

$$\dot{\mathbf{V}}(\mathbf{e}, \tilde{\mathbf{K}}_y, \tilde{\mathbf{K}}_r) = \dot{\mathbf{e}}^T \mathbf{P} \mathbf{e} + \mathbf{e}^T \mathbf{P} \dot{\mathbf{e}} + 2\mathbf{tr}(\tilde{\mathbf{K}}_y^T \boldsymbol{\Gamma}_{\boldsymbol{y}}^{-1} \dot{\hat{\mathbf{K}}}_y |\boldsymbol{\Lambda}|)$$
$$+ 2\mathbf{tr}(\tilde{\mathbf{K}}_r^T \boldsymbol{\Gamma}_r^{-1} \dot{\hat{\mathbf{K}}}_r |\boldsymbol{\Lambda}|)$$

$$= \left[\mathbf{A}_m \mathbf{e} + \mathbf{B}\boldsymbol{\Lambda}[\Delta\hat{\mathbf{K}}_r^T \mathbf{r} + \Delta\hat{\mathbf{K}}_x^T \mathbf{x}]\right]^T \mathbf{P}\mathbf{e} + \ldots$$
$$\mathbf{e}^T \mathbf{P} \left[\mathbf{A}_m \mathbf{e} + \mathbf{B}\boldsymbol{\Lambda}[\Delta\hat{\mathbf{K}}_r^T \mathbf{r} + \Delta\hat{\mathbf{K}}_x^T \mathbf{x}]\right] + \ldots$$
$$2\,\mathbf{tr}(\Delta\mathbf{K}_x^T \Gamma_x^{-1} \dot{\hat{K}}_x |\boldsymbol{\Lambda}|) + 2\,\mathbf{tr}(\Delta\mathbf{K}_r^T \Gamma_r^{-1} \dot{\hat{\mathbf{K}}}_r |\boldsymbol{\Lambda}|)$$

Stability Analysis

$$= \mathbf{e}^T(\mathbf{P}\,\mathbf{A}_m + \mathbf{A}_m^T\mathbf{P})\mathbf{e} + 2\mathbf{e}^T\mathbf{P}\mathbf{B}\mathbf{\Lambda}\left(\tilde{\mathbf{K}}_y^T\mathbf{y} + \tilde{\mathbf{K}}_r^T\mathbf{r}\right)$$
$$+2\,\mathbf{tr}\left(\tilde{\mathbf{K}}_y^T\mathbf{\Gamma}_{\mathbf{y}}^{-1}\dot{\hat{\mathbf{K}}}_y|\mathbf{\Lambda}|\right) + 2\,\mathbf{tr}\left(\tilde{\mathbf{K}}_r^T\mathbf{\Gamma}_r^{-1}\dot{\hat{\mathbf{K}}}_r|\mathbf{\Lambda}|\right)$$

$$= -\mathbf{e}^T\mathbf{Q}\mathbf{e} - 2\mathbf{e}^T\mathbf{P}\mathbf{B}\mathbf{\Lambda}\varepsilon_f(\mathbf{y}) + 2\mathbf{e}^T\mathbf{P}\mathbf{B}\mathbf{\Lambda}\tilde{\mathbf{K}}_y^T\mathbf{y}$$
$$+ 2\,\mathbf{tr}\left(\tilde{\mathbf{K}}_y^T\mathbf{\Gamma}_{\mathbf{y}}^{-1}\dot{\hat{\mathbf{K}}}_y\right) + 2\mathbf{e}^T\mathbf{P}\mathbf{B}\mathbf{\Lambda}\tilde{\mathbf{K}}_r^T\mathbf{r} + 2\,\mathbf{tr}\left(\Delta\mathbf{K}_r^T\mathbf{\Gamma}_r^{-1}\dot{\hat{\mathbf{K}}}_r\right)$$

Notice $x^T y = \mathbf{tr}\left(y\,x^T\right)$ from trace identity

Stability Analysis Cont'd

Therefore,

$$\begin{aligned}\dot{\mathbf{V}}(\cdot) &= -\mathbf{e}^T\mathbf{Q}\mathbf{e} - 2\mathbf{e}^T\mathbf{P}\mathbf{B}\boldsymbol{\Lambda}\varepsilon_f \\ &\quad + 2\,\mathbf{tr}\left(\tilde{\mathbf{K}}_y^T(\boldsymbol{\Gamma}_{\mathbf{y}}^{-1}\dot{\hat{\mathbf{K}}}_y + \mathbf{y}\mathbf{e}^T\mathbf{P}\mathbf{B}sgn(\boldsymbol{\Lambda})\right)|\boldsymbol{\Lambda}| \\ &\quad + 2\,\mathbf{tr}\left(\tilde{\mathbf{K}}_r^T(\boldsymbol{\Gamma}_r^{-1}\dot{\hat{\mathbf{K}}}_r + \mathbf{r}\mathbf{e}^T\mathbf{P}\mathbf{B}sgn(\boldsymbol{\Lambda})\right)|\boldsymbol{\Lambda}|\end{aligned}$$

where for a real-valued x, we have $x = \text{sgn}(x)|x|$.

- first two terms will be negative definite for all $\mathbf{e} \neq 0$
  - since $\mathbf{A}_m$ is Hurwitz
- other terms will be identically null if we choose the adaptation laws

$$\dot{\hat{\mathbf{K}}}_y = -\boldsymbol{\Gamma}_{\mathbf{y}}\mathbf{y}\mathbf{e}^T\mathbf{P}\,\mathbf{B}\text{sgn}(\boldsymbol{\Lambda}), \quad \dot{\hat{\mathbf{K}}}_r = -\boldsymbol{\Gamma}_r\mathbf{r}\mathbf{e}^T\mathbf{P}\,\mathbf{B}\,\text{sgn}(\boldsymbol{\Lambda})$$

Stability Results: Ogunmolu et al. (2017)

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

- $\{\lambda_{low}, \lambda_{high}\} \equiv$ min/max eigenvalues of Q and $\boldsymbol{\Lambda}$.
- $\dot{\mathbf{V}}(\cdot)$ is thus negative definite outside the compact set: $\chi = \left(\mathbf{e} : \|\mathbf{e}\| \le \frac{2\|\mathbf{P}\mathbf{B}\|\lambda_{high}(\boldsymbol{\Lambda})\varepsilon_{max}(\mathbf{y})}{\lambda_{low}(\mathbf{Q})}\right)$
  - *i.e.* **e** is **uniformly ultimately bounded**, or $\mathbf{y}(t) \to 0$ as $t \to \infty$.

Appendix C: 1-DOF Closed-Loop Control

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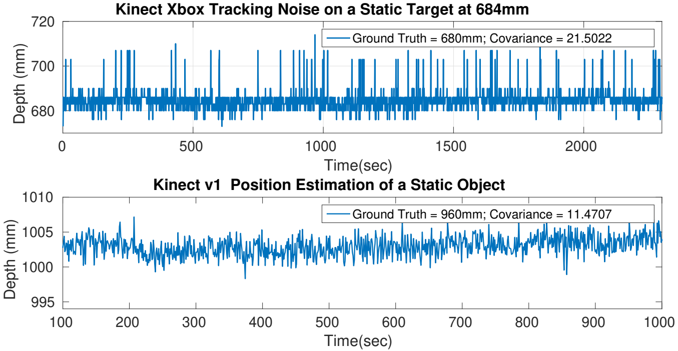
Head Pose Estimation: Sensor Fusion

Sensors' Noise Floor



Case for Sensed Observation Filtering

Optimal head state estimation and sensor fusion

- Find the observation estimates $\hat{\mathbf{x}}(i)$ that minimize the mean-square error from true measurement, *i.e.* ,

$$\hat{\mathbf{x}}(i|j) = \arg \min_{\hat{\mathbf{x}}(i|j) \in \mathbb{R}^n} \mathbb{E}\{(\mathbf{x}(i) - \hat{\mathbf{x}})^T(\mathbf{x}(i) - \hat{\mathbf{x}})|z(1), \cdots, z(j)\}$$

- Define the estimate error's covariance as

$$\mathbf{P}(i|j) \triangleq \mathbb{E}\{\left(\mathbf{x}(i) - \hat{\mathbf{x}}(i|j)\right)^T \left(\mathbf{x}(i) - \hat{\mathbf{x}}(i|j)\right) | Z^j\}. \qquad (2)$$

State estimation with Kalman filters

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Appendices

App A: 3DOF CL Control

App B: 1DOF

Kalman Filtering

Sensor Fusion

System Identification

App C: CCOARSE Actuator

- Assume state model, $\mathbf{F}(k)$
- For a discretized time interval ΔT between measurements, we define the state

$$\mathbf{x}(k) = \mathbf{F}(k)\mathbf{x}(k-1) + \mathbf{B}(k)\mathbf{u}_k + \mathbf{G}_k\mathbf{w}_k \tag{3}$$

  - with

$$\mathbf{F} = \begin{bmatrix} 1 & \Delta T \\ 0 & 1 \end{bmatrix} \tag{4}$$

Kalman filters

- (3) $\implies \mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{G}_k \mathbf{w}_k$
- $\mathbf{G}_k :=$ uncontrolled forces accelerating on head
- Head's acceleration, $a_k \sim \mathcal{N}(0, \sigma_a)$
- Setting $\mathbf{G}_k = \mathbf{I}_{2x2}$ and $\mathbf{w}(k) \sim \mathcal{N}(0, \mathbf{Q}(k))$
    - set $\mathbf{Q}(k)$ to a random walk sequence, $\mathbf{W}_k = [\frac{\Delta T^2}{2}, \Delta T]^T$

Kalman Filters Design

- Such that

$$\mathbf{Q} = \mathbf{W}\mathbf{W}^T {\sigma_a}^2 = \begin{bmatrix} \frac{\Delta T^4}{4} & \frac{\Delta T^3}{2} \\ \frac{\Delta T^3}{2} & \Delta T^2 \end{bmatrix} {\sigma_a}^2. \tag{5}$$

- Set the transfer matrix from the estimates, $\mathbf{x}(k)$, to observations, $z_1(k)$ and $z_2(k)$ according to

$$z_s = \mathbf{H}_s(k)\mathbf{x}(k) + v_s(k) \qquad s = 1, 2 \tag{6}$$

  - where $\mathbf{H}_s(k) = \begin{bmatrix} 1, & 0 \end{bmatrix}^T$ and $v_s(k) \sim \mathcal{N}(0, \sigma_{rs}^2)$

KF Priori and Posteriori State Estimates

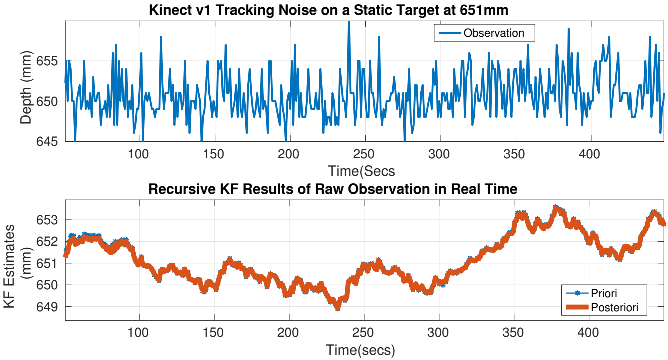
- **Prediction Phase:**

$$\begin{aligned} \hat{\mathbf{x}}_{k|k-1} &= \mathbf{F}\hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_k \mathbf{u}_k \\ \mathbf{P}_{k|k-1} &= \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k{}^T + \mathbf{Q}_k \end{aligned} \tag{7}$$

- **Update Phase:**

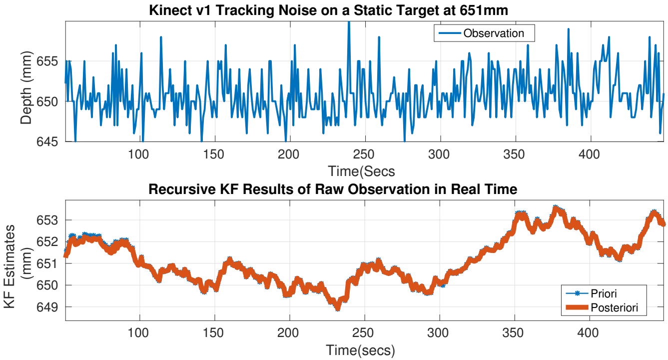
$$\begin{aligned} \mathbf{K}(k) &= \mathbf{P}(k|k-1)\mathbf{H}(k)^T [\mathbf{H}(k)\mathbf{P}(k|k-1)\mathbf{H}(k)^T + \mathbf{R}(k)]^{-1} \\ \hat{\mathbf{x}}(k|k) &= \hat{\mathbf{x}}(k|k-1) + \mathbf{K}(k)(\mathbf{z}(k) - \mathbf{H}(k)\hat{\mathbf{x}}(k|k-1)) \\ \mathbf{P}(k|k) &= (\mathbf{I} - \mathbf{K}(k)\mathbf{H}(k))\mathbf{P}(k|k-1) \end{aligned} \tag{8}$$

Xbox Filtering Results



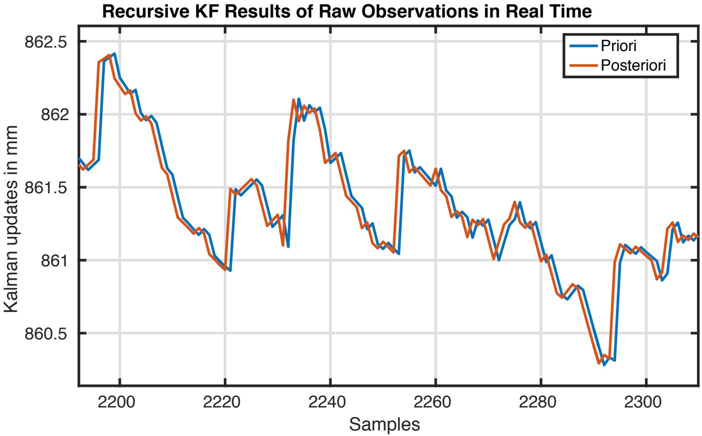
KF results of Xbox's observations

Kinect 2 Filtering Results



KF results of Kinect v1's observation

Filtering Results



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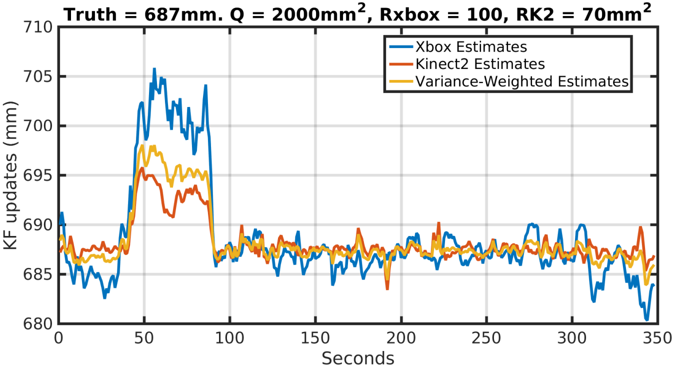
Global fusion of local tracks

- Fuse both updates with a variance-weighted average of each local track as follows,

$$\hat{\mathbf{x}}(F)(k|k) = \mathbf{P}(F)(k|k)\sum_{s=1}^{N}\left[\mathbf{P}(s)^{-1}(k|k)\hat{\mathbf{x}}(s)(k|k)\right]$$

$$\text{where } \mathbf{P}(F)(k|k) = \left[\sum_{s=1}^{N}\mathbf{P}(s)^{-1}(k|k)\right]^{-1}.$$

Track-to-track Fusion



Track-to-track fusion of both sensors' local track estimates.

Vision-based Control

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System Identification

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App C: CCOARSE Actuator

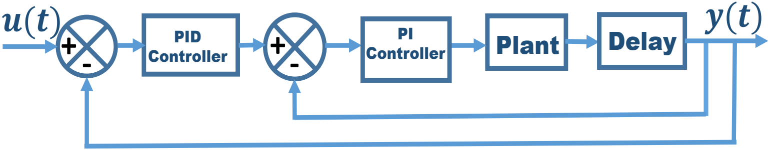
- From I/O data, estimate a model
- Find set of optimal model parameters via the minimization,

$$G(t) = \arg \min_{\theta} V_N(\theta, Z^N)$$

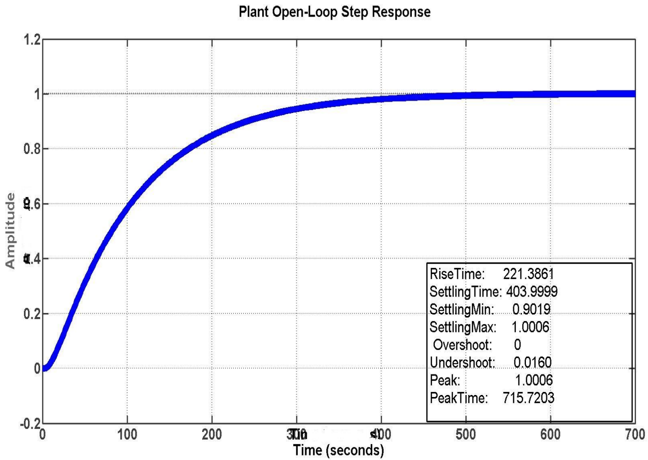
  - where $V_N(\theta, Z^N) = \sum_{k=1}^{\mathcal{K}} \sum_{i=1}^{n} \frac{1}{2} (\hat{y}_i(k) - y_i(k))^2$,
  - and $Z^N = \{u(1) \cdots u(N), \, y(1) \cdots y(N)\}$
- After a least squares minimization, we derive a state-space realization,

$$\begin{aligned} \mathbf{x}(k + Ts) &= \mathbf{Ax}(k) + \mathbf{Bu}(k) + \mathbf{Ke}(k) \\ \mathbf{y}(k) &= \mathbf{Cx}(k) + \mathbf{Du}(k) + \mathbf{e}(k) \end{aligned} \tag{9}$$

PID-PI Cascaded Controller



Open Loop Step Response



PI Closed-loop Step Response

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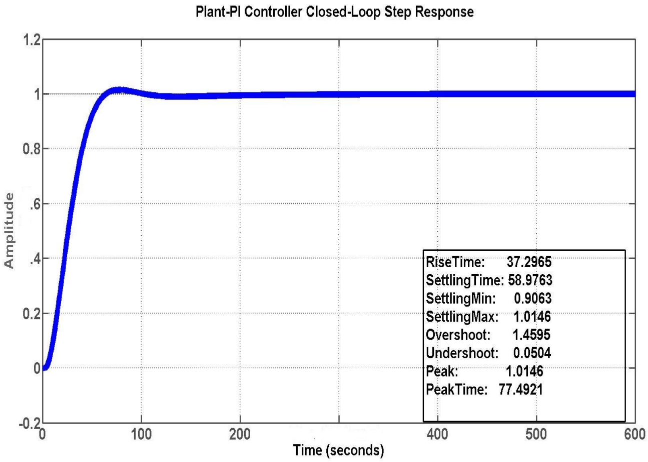
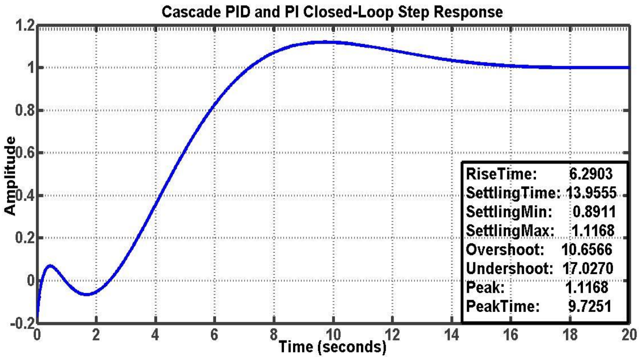
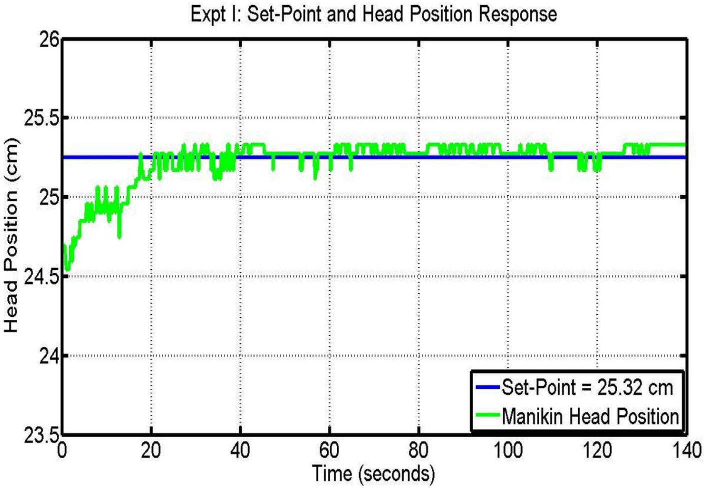


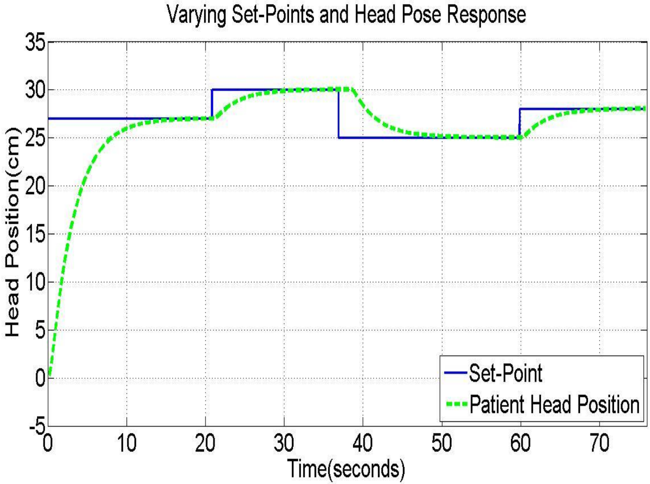
Cascaded PID-PI Closed-loop Step Response



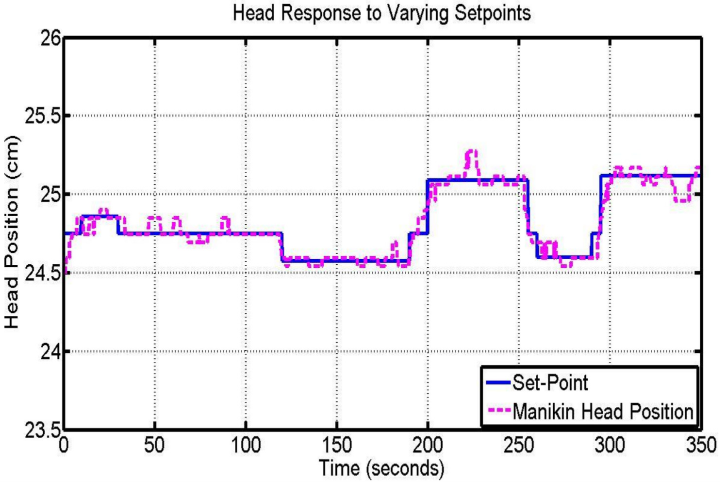
PI-PD Cascaded Controller Experimental Results



Varying Setpoint Simulation



Varying Setpoint Experiment



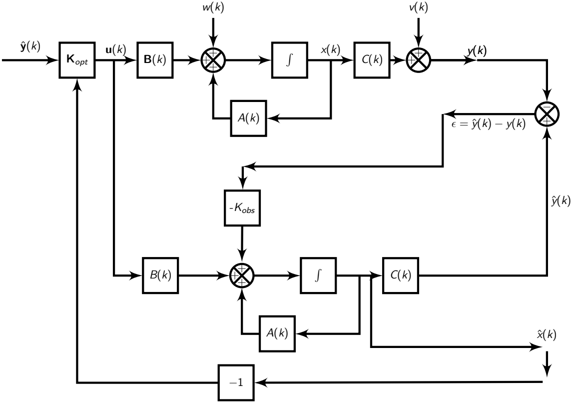
3-DOF Controller Design (IROS 2017)

- Posing the cost

$$J = \sum_{k=0}^{\mathcal{K}} x^T(k)\, Q\, x(k) + u(k)^T\, R\, u(k) + 2x(k)^T\, N\, u(k)$$

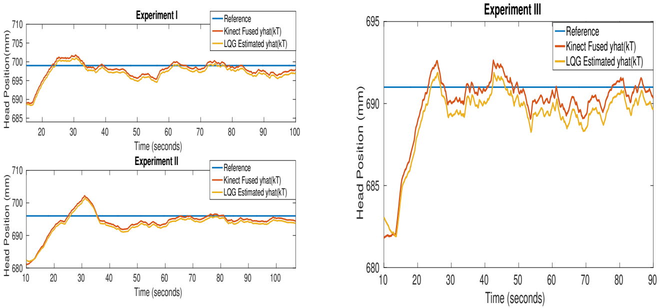
- we can obtain u as $\Delta u = \arg\min_{\Delta u} J$
- Δu is a future control sequence

Closed-loop control (Full state observer).



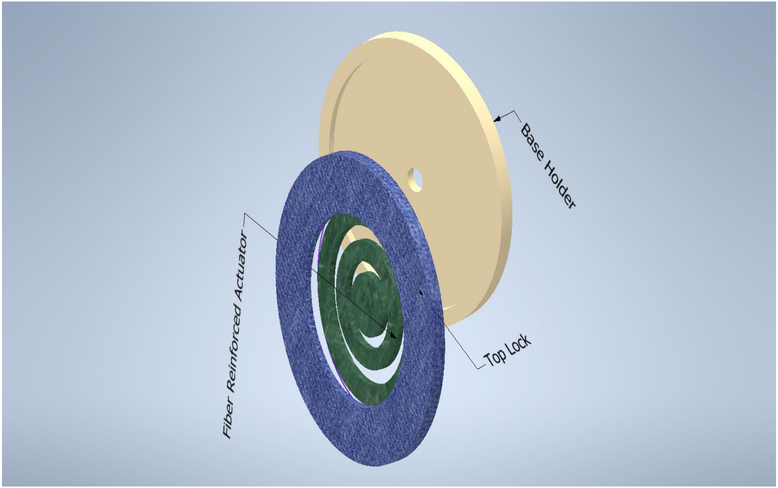
$$\hat{x}(k+1) = A(k)\hat{x}(k) - K_{obs}[C(k)\hat{x}(k) - y(k)] + B(k)u(k).$$

1-DOF Control Results



LQG Controller on mannequine head.

Appendix D: CCOARSE Actuator Schematic



Soft IK via Boundary Value Problem

- With Cauchy's laws of motion, solve boundary volume problem of traction

- 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
  - $\sigma_{rr}(r) = -\int_{r_i}^{r_o}[2C_1(\frac{r}{R^2} - \frac{R^4}{r^5}) + 2\,C_2\left(\frac{r^3}{R^4} - \frac{R^2}{r^3}\right)]dr$
  - $\sigma_{rr}(r) = \int_{R_i}^{R_o}[2C_1\left(\frac{1}{r} - \frac{R^6}{r^7}\right) - 2C_2\left(\frac{R^4}{r^5} - \frac{r}{R^2}\right)]\,dr$
- With $\sigma_{rr|R=R_i} = -P_{atm} - P$ and setting $P_{atm} = 0$, we find
  - $P(r) = \int_{r_i}^{r_o}[2C_1(\frac{r}{R^2} - \frac{R^4}{r^5}) + 2\,C_2\left(\frac{r^3}{R^4} - \frac{R^2}{r^3}\right)]dr$
  - $P(r) = \int_{R_i}^{R_o}[2C_1\left(\frac{1}{r} - \frac{R^6}{r^7}\right) - 2C_2\left(\frac{R^4}{r^5} - \frac{r}{R^2}\right)]\,dr$