SoftNeuroAdapt: A 3-DoF Neuro-Adaptive Healthcare System

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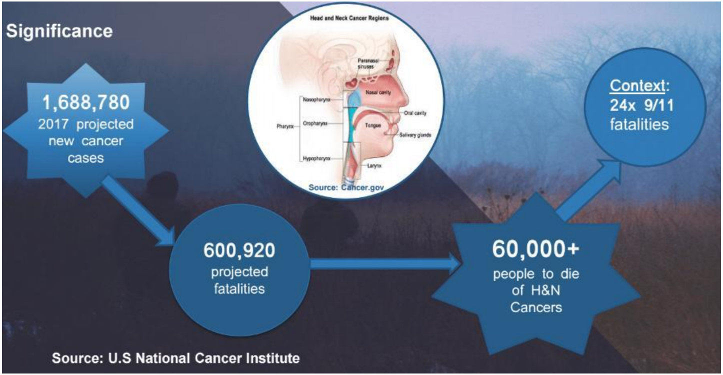
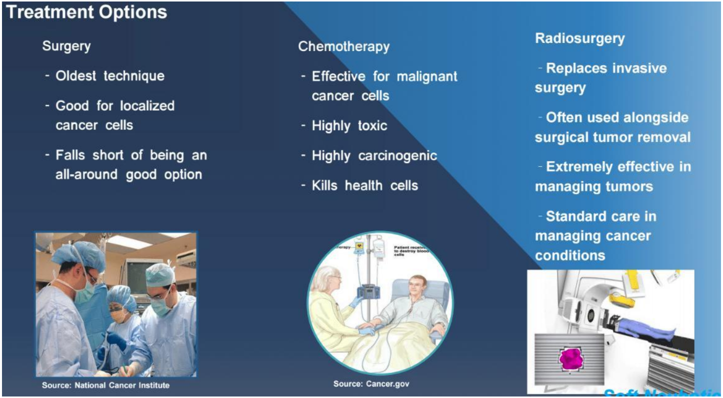
Background

- Cancers of the head and neck (H&N)



Treatment Options



- Radiotherapy treatment is the most effective

Radiotherapy Treatment

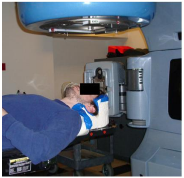
- 3D CT/MRI scans too determine treatment plan
- Requires head landmarks + mechanical immobilization objects
- Employs ionizing radiation to destroy abnormal tissues
- Involves less precise radiation dose over many days/weeks

Radiation Therapy Drawbacks

- Rigid immobilization
  - LINAC angle misalignments cause negative dosimetry effects [Xing (2000)]
  - treatment discomfort from long hours of surgery
  - requires inconvenient face masks
- Cyberknife
  - incompatible with conventional LINACs used at the majority of cancer centers.
  - real-time x-ray motion tracking introduces extra radiation-dose
- Novalis ExacTrac Robotic Tilt Module
  - only uses pre-treatment images
  - only provides rigid motion compensation

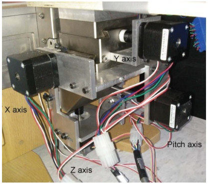
Frameless/Maskless Radiotherapy

(Cervino, L. 2010)



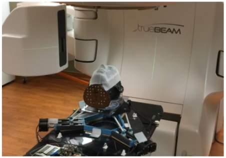
Feasibility evaluation

(Liu, X. 2015)



4-D robotic stage couch

(Ostyn, M. 2017)



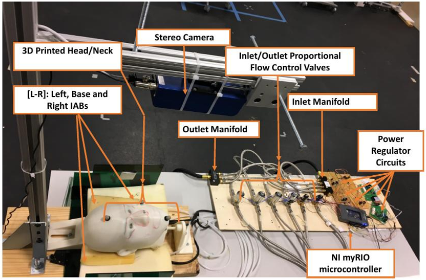
6-DoF rigid robotic couch

Solution: Soft-Robot Position Correcting Systems

- Eliminate rigid frames and metallic rings
  - Maskless and frameless positioning system ✓
- Eliminate attenuation of X-Ray beams
  - Separate electromechanical components from patient actuation ✓
  - Explore soft polymer actuators ✓
- Control design
  - Feedback control + optimal regulation + robustness to disturbance ✓
- Adapt for changing parameters in system's dynamics within control law
  - Neural network function approximator ✓

Hardware set-up

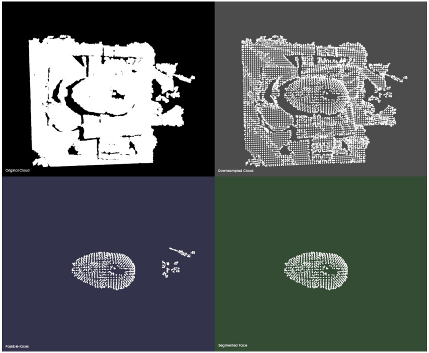
- **System Components**
  - 3D printed head
    - ≈ size of an average adult male
  - 3 custom-designed inflatable air bladders (IABs)
    - made from elastomeric polymers
    - encased in a breathable foam pad for soft actuation
  - A regulated air canister supplied constant air pressure at 15 psi
  - Proportional solenoid valves regulate amount of air supply through silicone hoses



3-DoF Motion Correction System

Vision-based head pose estimation

- Acquire face point cloud from stereo camera
- Find edges of 2D planar regions in scene structure (Torr and Zisserman, 2000)
  - bound resulting plane indices with their 2D convex hull
- Extract face and face-height neighbors into a predefined 2D prismatic model (Rusu, R. et. al, 2008)
- Cluster extracted points based with Euclidean Clustering (Rusu Thesis)



[Top-left]: Dense point cloud of the scene.
[Top-right]: Downsampled cluttered cloud of the scene.
[Bottom-left]: Using RANSAC, we searched for 2D plane candidates in the scene and compute the convex hull of found planar regions. We then extrude point indices in the hull to a prismatic polygonal model to give the face region.
[Bottom-right]: An additional step clusters the resultant cloud based on a user-defined Euclidean distance.

Head Pose Estimation

- Goal: Compute optimal translation and rotation of the head
  - from a model point set $\mathbf{X} = \{\overrightarrow{x}_i\}$ to a measured point set $\mathbf{P} = \{\overrightarrow{p}_i\}$, where $N_x = N_p = 3$,
  - point $\overrightarrow{x}_i \in \mathbf{X}$ has the same index as $\overrightarrow{p}_i \in \mathbf{P}$
  - set three points on the table scene as model points
- Obtain centroid of segmented cloud from the previous scene
  - set this as measured point
- Compute the covariance matrix, Σ_{px}, of $\mathbf{P}$ and $\mathbf{X}$
  - extract cyclic components of the skew-symmetric matrix as Δ
  - form symmetric 4×4 matrix $Q(\Sigma_{px})$
    - $\mathbf{Q}(\boldsymbol{\Sigma}_{px}) = \begin{bmatrix} \mathbf{tr}(\boldsymbol{\Sigma}_{px}) & \boldsymbol{\Delta}^T \\ \boldsymbol{\Delta} & \boldsymbol{\Sigma}_{px} + \boldsymbol{\Sigma}_{px}^T - \mathbf{tr}(\boldsymbol{\Sigma}_{px})\mathbf{I}_3 \end{bmatrix}$

Head Pose Estimation (Besl & McKay, '92)

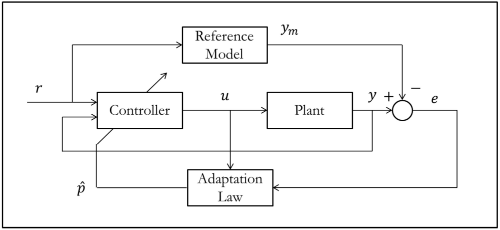
- The unit eigenvector, q_R, that corresponds to the maximum eigenvalue of $\mathbf{Q}(\Sigma_{px})$ is selected as the optimal rotation quaternion;
- Optimal translation vector given by
  - $\overrightarrow{q}_T = \overrightarrow{\mu}_x - \mathbf{R}(\overrightarrow{q}_R)\overrightarrow{\mu}_p$
- μ_x and μ_p are the mean of point sets **X** and **P** respectively
- Face pose defined by tuples $[q_T, q_R] = \{x, y, z, \theta, \phi, \psi\}$ with respect to the world frame
- We control z, θ, ϕ (i.e. z, roll, and pitch states)

Control Overview

- State feedback and feedforward regulation problem
- Adaptation mechanism based on an estimation of the head pose given a priori information about the system's states and past control actions
  - $Z^N = \{u(k), u(k-1), \ldots u(k-n_u), y(k), \ldots, y(k-n_y)\}$
  - Fix a persistently exciting input signal $u_{ex} \in L_2 \cap L_\infty$ to excite the nonlinear modes of the system
    - Approximate nonlinear system by a long short-term memory, Hochreiter (1997)
    - Parameterize network's last layer with a fully connected layer that outputs control torques to the valves

Control Design Objectives

- Stabilize system states, $\mathbf{y} = \left[x, y, z, \theta, \phi, \psi\right]^T$
- Provide closed loop tracking given a desired trajectory, $\mathbf{r}$
- Robustify system to (non-)parametric uncertainties
    - changing head shapes, size and other anatomic/tumor variations



Indirect MRAC system. (Source mdpi.com)

Model Reference Adaptive Control

- Model head and bladder dynamics as
  - $\dot{\mathbf{y}} = \mathbf{A}\mathbf{y} + \mathbf{B}\boldsymbol{\Lambda}\left(\mathbf{u} - f(\mathbf{y})\right) + \mathbf{w}(k)$
    - $\mathbf{A}$, $\boldsymbol{\Lambda}$ unknown, $\mathbf{B}$, $\text{sgn}\boldsymbol{\Lambda}$ known
    - $f(\mathbf{y}) \triangleq$ nonlinear function to be adapted for
    - $\mathbf{x} \triangleq$ tuple containing past controls and current outputs
- Approximate $f(\mathbf{y})$ by a neural network with continuous memory states
  - $\hat{f}\left(\mathbf{u}(k-d), \mathbf{y}(k), \mathbf{w}(k)\right)$ is realized with a *long-short term memory* cell (Horchreiter and Schmidhuber, '91, '97)
  - **purpose**: remember good adaptation gains

Assumptions

- A dynamic RNN with N neurons, $\varphi(\mathbf{x})$, exists
  - maps from a compact input space $\mathbf{u} \subset \mathbb{U}$ to $\mathbf{y} \subset \mathbb{Y}$ on the Lebesgue integrable functions within $[0, T]$ or $[0, \infty)$
- $f(\mathbf{x})$ is exactly $\Theta^T \Phi(\mathbf{x})$
  - f has coefficients $\Theta \in R^{N \times m}$ and a Lipschitz-continuous vector of basis functions $\Phi(\mathbf{x}) \in R^N$
- Inside a ball $\mathbf{Y}_R$ with known, finite radius R,
  - an ideal neural network (NN) approximation $f(\mathbf{x}) : R^n \to R^m$, is realized to a sufficient degree of accuracy, $\varepsilon_f > 0$;
- Outside $\mathbf{Y}_R$,
  - the NN approximation error can be upper-bounded by a known unbounded, scalar function $\varepsilon_{max}(\mathbf{x})$;
  - $\|\varepsilon(\mathbf{x})\| \leq \varepsilon_{max}(\mathbf{x}), \quad \forall \quad \mathbf{x} \in \mathbf{Y}_R$;
- There exists an exponentially stable reference model
  - $\dot{\mathbf{y}}_m = \mathbf{A}_m y_m + \mathbf{B}_m \mathbf{r}$

Control Design Objectives

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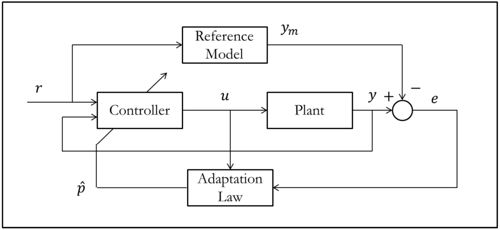


Indirect MRAC system. (Source mdpi.com)

Adaptive Neuro-Control Scheme

- Set control law in terms of parameter estimates from the neural network weights and Lipschitz basis functions
  - $\Phi(\mathbf{y}) = \{\mathbf{y}(k-d), \cdots, \mathbf{y}(k-d-4), \mathbf{u}(k-d) \cdots \mathbf{u}(k-d-5)\}$
  - *i.e.* network looks back in time by 5 time steps at every instant, and then makes a prediction
- Derive adaptive adjustment mechanism from Lyapunov analysis for Adaptive Control (Parks, P., 1966)

Controller formulation

- $\mathbf{u} = \underbrace{\hat{\mathbf{K}}_y^{\mathbf{T}} \mathbf{y}}_{\text{state feedback}} + \underbrace{\hat{\mathbf{K}}_r^{\mathbf{T}} \mathbf{r}}_{\text{optimal regulator}} + \underbrace{\hat{f}(\mathbf{y}, \mathbf{u})}_{\text{approximator}}$
  - $\hat{\mathbf{K}}_y$ and $\hat{\mathbf{K}}_r$ are adaptive gains to be designed

Term Contributions

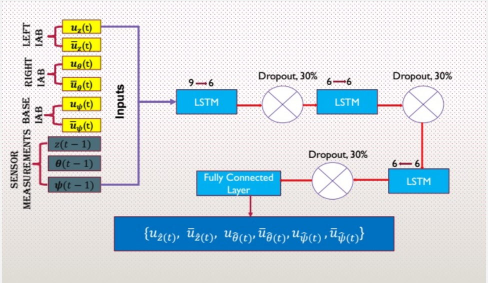
- $\hat{\mathbf{K}}_y^{\mathbf{T}} \mathbf{y}$ term keeps the states of the approximation set $\mathbf{y} \in \mathbf{B}_R$ stable,
- $\hat{\mathbf{K}}_r^{\mathbf{T}} \mathbf{r}$ term causes the states to follow a given reference trajectory
- Function approximator $\hat{f}(\cdot)$ ensures states that start outside the approximation set $\mathbf{y} \in \mathbf{B}_R$ converge to $\mathbf{B}_R$ in finite time

Adaptive Control Formulation

- Assume model matching conditions
  - such that $\hat{\mathbf{K}}_y = \mathbf{K}_y$, and $\hat{\mathbf{K}}_r = \mathbf{K}_r$ (ideally)
- Realize the approximator as $\hat{f}(\mathbf{x}) = \hat{\mathbf{\Theta}}^T \mathbf{\Phi}(\mathbf{y}) + \varepsilon_f(\mathbf{y})$
  - $\hat{\mathbf{\Theta}}^T$ denotes the vectorized weights of the neural network
  - $\mathbf{\Phi}(\mathbf{y})$ denotes the vector of lagged inputs and output,
  - $\varepsilon_f(\mathbf{y})$ is the approximation error.
  - $\mathbf{\Phi}(\mathbf{x}) = \{\mathbf{x}(k-d) \cdots \mathbf{x}(k-d-4), \mathbf{u}(k-d) \cdots \mathbf{u}(k-d-5)\}$

Neural Network Model

Neural Net Architecture



- input: lagged vector of past observations and current control actions
- repeat $\times$ 3
  - pass input through an lstm cell
  - followed by 30% dropout
- output will be control predictions directly fed as valve voltages

Closed-loop dynamics

- State closed loop dynamics is
  $\dot{\mathbf{y}} = \mathbf{A} + \mathbf{B}\Lambda(\hat{\mathbf{K}}_y^T \mathbf{y} + \mathbf{B}\Lambda(\hat{\mathbf{K}}_r^T \mathbf{r} + \varepsilon_f))$
  - $\mathbf{A}$ and Λ are unknown matrices.
  - sign of Λ is known
  - $\hat{\mathbf{K}}_y^T$ and $\hat{\mathbf{K}}_r^T$ are adaptation gains to be determined
- Generalized error state vector: $\mathbf{e}(k) = \mathbf{y}(k) - \mathbf{y}_m(k)$
  - with dynamics $\dot{\mathbf{e}}(k) = \mathbf{A}_m \mathbf{e}(k) + \mathbf{B}\Lambda[\tilde{\mathbf{K}}_r^T \mathbf{r} + \tilde{\mathbf{K}}_y^T \mathbf{y} - \varepsilon_f]$
  - $\mathbf{A}_m$ is Hurwitz and known, $\mathbf{B}$ is known.
  - $\mathbf{y}_m$ is assumed to be a linear model-following model of the form, $\dot{\mathbf{y}}_m = \mathbf{A}_m \mathbf{y}_m + \mathbf{B}\,\mathbf{r}$

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 $\mathbf{r}$.
- **Proof**:
  - 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

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

Stability proof

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

$$= \left[\mathbf{A}_m \mathbf{e} + \mathbf{B}\mathbf{\Lambda}[\Delta \hat{\mathbf{K}}_r^T \mathbf{r} + \Delta \hat{\mathbf{K}}_x^T \mathbf{x}]\right]^T \mathbf{P}\mathbf{e} + \ldots$$

$$\mathbf{e}^T \mathbf{P} \left[\mathbf{A}_m \mathbf{e} + \mathbf{B}\mathbf{\Lambda}[\Delta \hat{\mathbf{K}}_r^T \mathbf{r} + \Delta \hat{\mathbf{K}}_x^T \mathbf{x}]\right] + \ldots$$

$$2\,\mathbf{tr}(\Delta \mathbf{K}_x^T \Gamma_x^{-1} \dot{\hat{K}}_x |\mathbf{\Lambda}|) + 2\,\mathbf{tr}(\Delta \mathbf{K}_r^T \Gamma_r^{-1} \dot{\hat{\mathbf{K}}}_r |\mathbf{\Lambda}|)$$

Stability Analysis

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

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

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

Stability Analysis Cont'd

Therefore,

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

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

- 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

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

Control gains

Therefore,

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

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

Experimental Results

- Head 3-DOF pose made up of tuples $\{z(k), \theta(k), \phi(k)\}$
  - *i.e.* roll, pitch and yaw
  - sample from the parameters of the network
- Set $\hat{f}(\cdot)$ to the fully connected layer of samples from the network
- Control law is implemented on the ROS middleware
- Gains $\hat{\mathbf{K}}_y$ and $\hat{\mathbf{K}}_r$ found by solving the ODEs iteratively
  - using a single step of the integral of the solutions to $\dot{\hat{\mathbf{K}}}_y(t)$, $\dot{\hat{\mathbf{K}}}_r(t)$
  - implemented using Runge-Kutta Dormand-Prince 5 ODE-solver available in the Boost C++ libraries

Results

- Sample from trained network parameters
- Set $\hat{f}(\cdot)$ to fully connected layer of network
- $\mathbf{y}_m$ is computed based on
  - $\mathbf{y}_m(t) = e^{\mathbf{A}_m t}\mathbf{y}_m(0) + \int_0^t e^{\mathbf{A}_m(t-\tau)}\mathbf{B}_m\mathbf{r}(\tau)d\tau$
- Set $\mathbf{y}_m(0) = \mathbf{y}(0)$ at t = 0
- For a nonnegative $\mathbf{Q}$ and a positive definite $\mathbf{P}$,
  - the pair $(\mathbf{Q}, \mathbf{A}_m)$ will be observable (LaSalle's theorm)
  - so that the dynamical system is globally asymptotically stable.
- Pick a positive definite, $\mathbf{Q} = diag(100, 100, 100)$ for the dissipation energy
- Set $\boldsymbol{\Lambda} = \mathbf{I}_{3\times 3}$

Results

- 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
  - two valves create a difference in air mass within each IAB at any given time
  - set

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

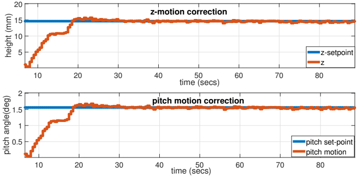
- B maps to the 3-axes controllers

$$\begin{bmatrix} u_z & u_\theta & u_\psi \end{bmatrix}^T$$

- non-zero terms are the max. duty-cycle to valves based on the software configuration of the NI RIO PWM generator

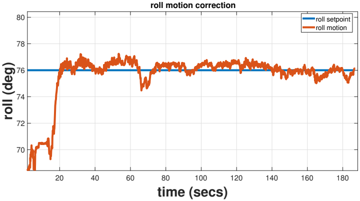
Results

- Performance of the controller when commanded to move head from $[z, \theta, \phi]^T = [2.5mm, .25^o, 35^o]^T$ to $[14mm, 1.6^o, 45^o]^T$.



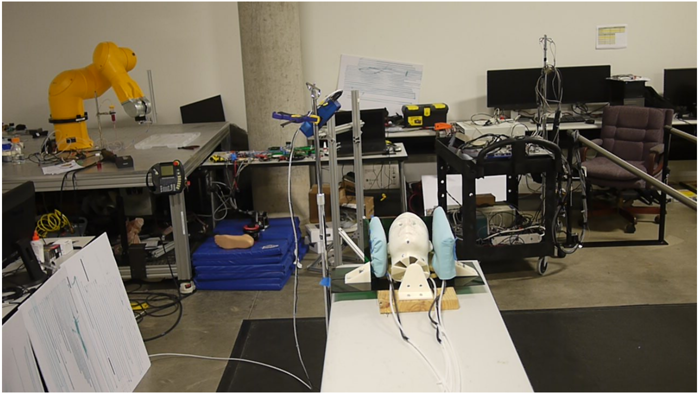
- strong steady-state convergence along z and pitch axes
- 20 second rise time

- Performance on head roll angle



- Need for separation of coupled dynamics
- Results show effectiveness of control law along the physically realizable axes of motions

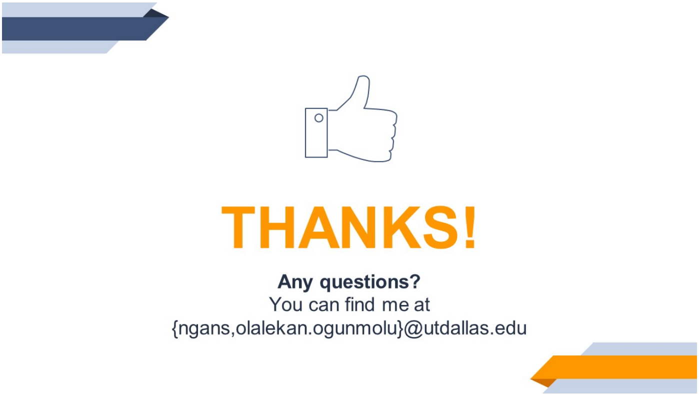
Video of Results



Results and Analysis

- Desired actuation axes coupled
  - there is a limited reachable space with the IABs
  - perform open-loop experiments to ensure pose is feasible
- Performance of the controller when commanded to move the head from $[z, \theta, \phi]^T = [2.5mm, .25^o, 35^o]^T$ to $[14mm, 1.6^o, 45^o]^T$.
  - strong steady-state convergence along z and pitch axes
  - 20 second rise time

Thanks!


THANKS!
Any questions?
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