The Future of Robotics/Automation & Course Review

METR 4202: **Robotics** & Automation

Dr Surya Singh -- Lecture # 13

October 26, 2016

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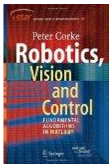
http://robotics.itee.uq.edu.au/~metr4202/

[http://**metr4202.com**]

Schedule of Events

Week	Date	Lecture (W: 12:05-1:50, 50-N202)
1	27-Jul	Introduction
2	3-Aug	Representing Position & Orientation & State (Frames, Transformation Matrices & Affine Transformations)
3	10-Aug	Robot Kinematics Review (*& Ekka Day*)
4	17-Aug	Robot Inverse Kinematics & Kinetics
5	24-Aug	Robot Dynamics (Jacobeans)
6	31-Aug	Robot Sensing: Perception & Linear Observers
7	7-Sep	Robot Sensing: Single View Geometry & Lines
8	14-Sep	Robot Sensing: Feature Detection
9	21-Sep	Robot Sensing: Multiple View Geometry
	28-Sep	*Study break*
10	5-Oct	Motion Planning
11	12-Oct	Probabilistic Robotics: Localization & SLAM
12	19-Oct	Probabilistic Robotics: Planning & Control (State-Space/Shaping the Dynamic Response/LQR)
13	**26-Oct**	**The Future of Robotics/Automation + Challenges & Course Review**

Follow Along Reading:



Robotics, Vision & Control
by Peter Corke

Also online:SpringerLink

UQ Library eBook: 364220144X

Today

- Vision-Based Control
  - §15.1-15.3 (pp. 456-473)

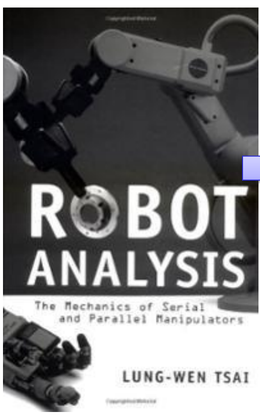
➔ **Review** 🡸

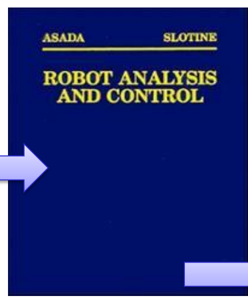
- SLAM
  - pp. 123-4 (§6.4-6.5)

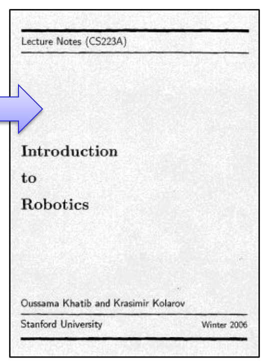
- Everything? ☺
  - Many references…

Next Time

Reference Material

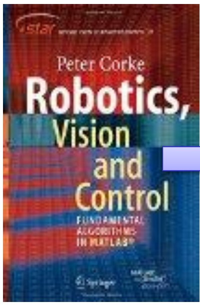


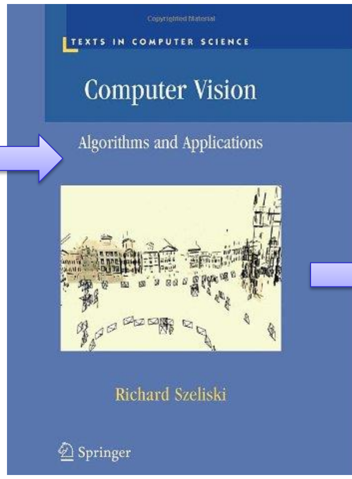




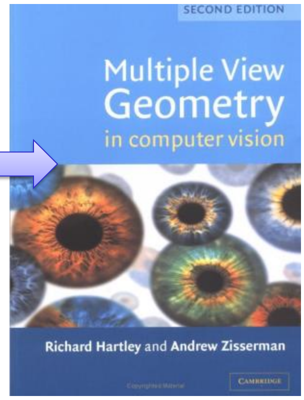
On class webpage
Password: metr4202

Reference Material



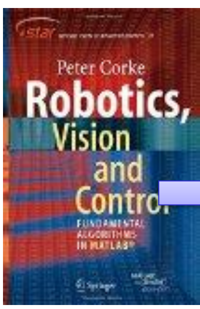


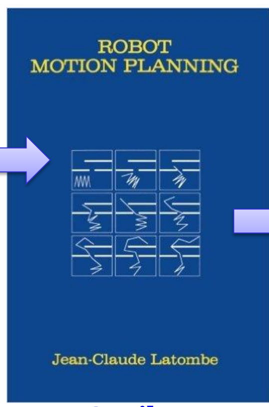
[UQ Library/ SpringerLink]



[UQ Library]
(ePDF)

Reference Material





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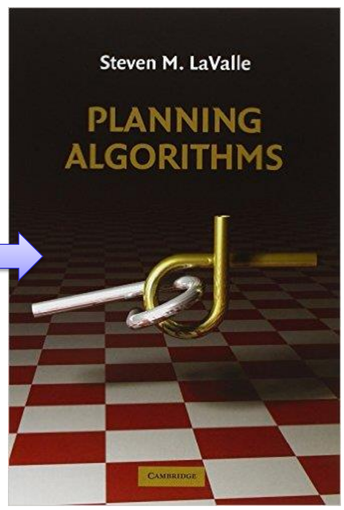
(TJ211.4 .L38 1991)



[UQ Library / Online (PDF)]

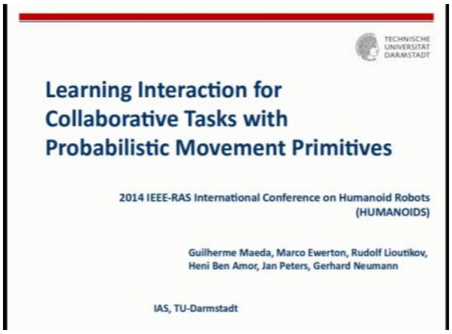
Cool Robotics Share

- Interactive Mobile Robots

- New transmissions

Source: (top) https://youtu.be/hX6pFcfr29c | (bottom) http://spectrum.ieee.org/automaton/robotics/robotics-hardware/sri-demonstrates-abacus-rotary-transmission

HRI: Semi-Autonomous Robots Learning Interaction for Collaborative Tasks



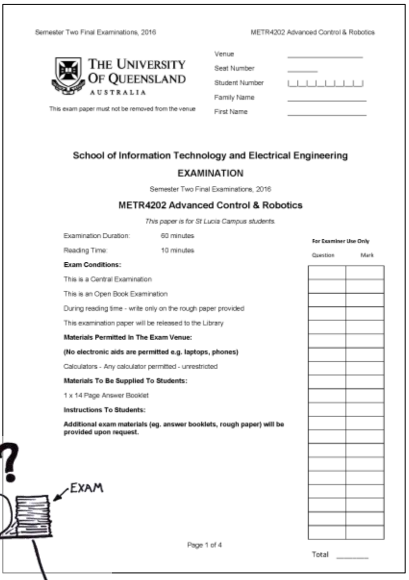
Maeda, G., *et al.* "Learning interaction for collaborative tasks with probabilistic movement primitives." 2014 *IEEE-RAS International Conference on Humanoid Robotics*. IEEE, 2014. https://youtu.be/2Ok6KQQQDNQ

Final Exam!

- 4 Questions | 60 Minutes
- **Open Book**
- Similar in nature to the 2015 Quiz

Topics:

- Position, orientation and location in space
- Robot analysis (forward/Inverse kinematics, recursive Newton-Euler formulations, etc.)
- Sensing geometry (including camera calibration)
- Multiple-view geometry
- Motion planning and control



Semester Two Final Examinations, 2016 METR4202 Advanced Control & Robotics

THE UNIVERSITY OF QUEENSLAND AUSTRALIA

This exam paper must not be removed from the venue

Venue ____
Seat Number ____
Student Number ____
Family Name ____
First Name ____

School of Information Technology and Electrical Engineering

EXAMINATION

Semester Two Final Examinations, 2016

METR4202 Advanced Control & Robotics

This paper is for St Lucia Campus students.

Examination Duration: 60 minutes

Reading Time: 10 minutes

Exam Conditions:

This is a Central Examination

This is an Open Book Examination

During reading time - write only on the rough paper provided

This examination paper will be released to the Library

Materials Permitted In The Exam Venue:

(No electronic aids are permitted e.g. laptops, phones)

Calculators - Any calculator permitted - unrestricted

Materials To Be Supplied To Students:

1 x 14 Page Answer Booklet

Instructions To Students:

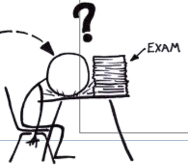
Additional exam materials (eg. answer booklets, rough paper) will be provided upon request.

For Examiner Use Only

Question	Mark

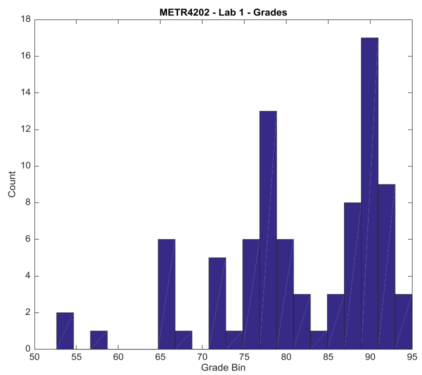
Total ____

Page 1 of 4



Grades!

- Lab 1



- MEAN: 82 | STD: 10
- MIN: 52 | MAX: 95
- MEDIAN: 83.5

- Lab 2

Coming Soon!

PS: For those who have not LAB 2 “PAF-ed” please do so by tonight! ☺

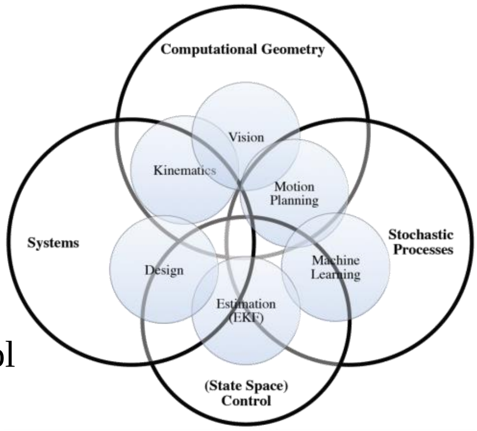
Some 2017 Robotics Thesis Topics

Projects (2017 | RDL | S. Singh)	
ID	**Title**
1	Light Fields in Motion
2	Image Sensing and Control
3	One Sweet Robot
4	Remote Access CT imaging Laboratory for clinical skills education and training
5	Semi-Automatic Tracking of Athletes Diving using Pre-selected Keypoints
7	(RDL*) Dermatology Outback
8	Interactive Ball / Beeper Ball - Smart Tones
9	Affine Breathing: Tracking
10	Underactuated Robotics: Katita Walks The Line
11	Assistive Ultrasound Support
13	SuperResolve 3D [NEW]
14	**Privacy Preserving Roadmap Planning [NEW]**
15	Color My World (Art Meets Robotics) [NEW]
16	**Robots: In Play (Probabilistically) [NEW]**
17	Project with Sound and Hearing and Mechatronics [NEW]
18	**Biomedical Engineering Meets Robotics [NEW] [ARC DP co-funding]**
19	(Virtual) Robotics and Experimental Platform [NEW]
20	BYO Robot Project [NEW]

Learning Objectives

Robotics:
Facets of overarching principles

- Scene Geometry
- Structure | Unstructured
- Adaptive models for control
- Interactions: Deterministic | Probabilistic



Estimation

Along multiple dimensions

State Space

- We collect our set of uncertain variables into a vector …
  $\mathbf{x} = [x_1, x_2, \ldots, x_N]^T$
- The set of values that **x** might take on is termed the *state space*
- There is a *single* true value for **x**,
  but it is unknown

State Space Dynamics

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$
$$\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u}$$

$$H(s) = C(sI - A)^{-1}B$$

Measured versus True

- Measurement errors are inevitable
- So, add Noise to State...
  - State Dynamics be $\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} + w$
    $\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u} + v$
- Can represent this as a "Normal" Distribution

$$\mathcal{N}(x;\mu,\sigma) = \frac{1}{\left(\sqrt{2\pi}\right)\sigma}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

Recovering The Truth

- Numerous methods
- Termed "Estimation" because we are trying to estimate the truth from the signal
- A strategy discovered by Gauss
- Least Squares in Matrix Representation

$$\begin{bmatrix} p_0 \\ p_1 \end{bmatrix} = \begin{bmatrix} n & \sum_1^n t_i \\ \sum_1^n t_i & \sum_1^n t_i^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum_1^n z_i \\ \sum_1^n t_i z_i \end{bmatrix}$$

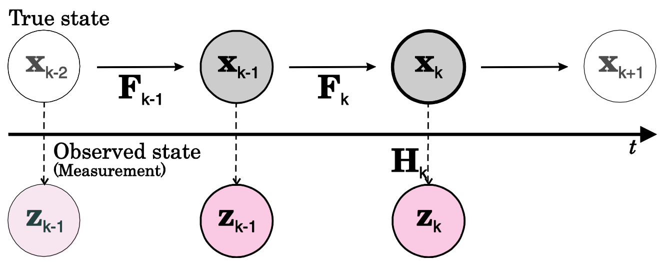
Recovering the Truth: Terminology

$$\dot{\mathbf{x}} = \mathbf{F}\mathbf{x} + \mathbf{G}\mathbf{u} + \mathbf{w}$$

$$\mathbf{z} = \mathbf{H}\mathbf{x} + \mathbf{v}$$

$\mathbf{x}$: the state vector
$\mathbf{x}_{A|B}$: the state of $\mathbf{x}$ at time A based on data taken up to time B
$\hat{\mathbf{x}}$: estimate of the true state vector
$\mathbf{F}$: system dynamics matrix in continuous time (equivalent to $\mathbf{A}$ in Eq. 1)
$\mathbf{G}$: system control matrix relating deterministic input, $\mathbf{u}$, to the state (equivalent to $\mathbf{B}$ in Eq. 1)
$\mathbf{H}$: measurement matrix in continuous time (equivalent to $\mathbf{C}$ in Eq. 2)
$\mathbf{F}_i$: system model in **discrete** time at $t = t_i$
$\mathbf{H}_i$: measurement model in **discrete** time at $t = t_i$
$\mathbf{P}_i$: estimate covariance in **discrete** time at $t = t_i$
$\mathbf{w}$: process uncertainty (noise) vector (of type $\mathcal{N}(0, s)$)
$\mathbf{Q}$: process noise matrix, $\mathbf{Q} = E\left[ww^\mathsf{T}\right]$
$\mathbf{Q}_i$: $\mathbf{Q}$ in discrete time at $t = t_i$
$\mathbf{v}$: measurement noise vectors (of type $\mathcal{N}(0, \sigma)$)
$\mathbf{R}_i$: the measurement variance matrix, $\mathbf{R} = E\left[vv^\mathsf{T}\right]$, in discrete time at $t = t_i$

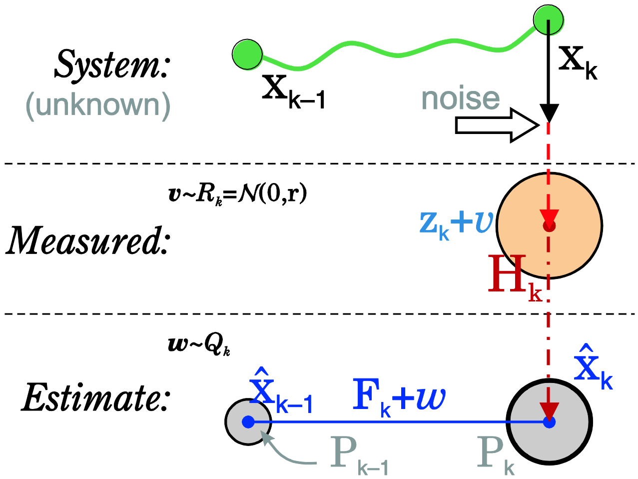
General Problem…



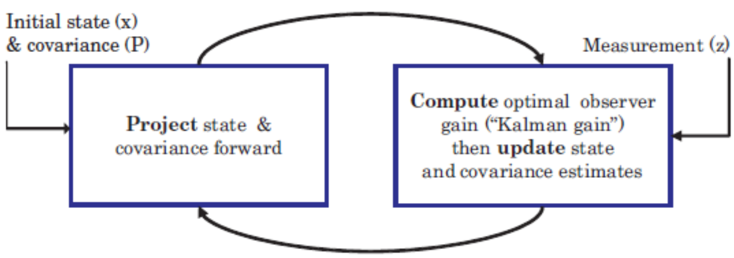
Duals and Dual Terminology

	Estimation		Control
Model:	$\dot{\mathrm{x}} = \mathbf{F}\mathrm{x}$ (discrete: $\mathrm{x} = \mathbf{F}_k \mathrm{x}$)	$\leftrightarrow$	$\dot{\mathrm{x}} = \mathbf{A}\mathrm{x},\ \mathbf{A} = \mathbf{F}^T$
Regulates:	P (covariance)	$\leftrightarrow$	M (performance matrix)
Minimized function:	Q (or GQG^T)	$\leftrightarrow$	V
Optimal Gain:	K	$\leftrightarrow$	G
Completeness law:	Observability	$\leftrightarrow$	Controllability

Estimation Process in Pictures



Kalman Filter Process



KF Process in Equations

Prediction: $\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1|k-1},$ (state prediction)

$\mathbf{P}_{k|k-1} = \mathbf{Q}_{k-1} + \mathbf{F}_{k-1}\mathbf{P}_{k-1|k-1}\mathbf{F}^{\mathsf{T}}{}_{k-1},$ (covariance prediction)

Kalman Gain: $\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}^{\mathsf{T}}[\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^{\mathsf{T}} + \mathbf{R}_k]^{-1},$

Update: $\mathbf{P}_{k|k} = [\mathbf{I} - \mathbf{K}_k\mathbf{H}]\mathbf{P}_{k|k-1},$ (covariance update)

$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k(\mathbf{z}_k - \mathbf{H}\hat{\mathbf{x}}_{k|k-1})$ (state update)

KF Considerations

$$\underbrace{\hat{\mathbf{x}}_{k|k-1}}_{n\times 1} = \underbrace{\mathbf{F}_{k-1}}_{n\times n}\hat{\mathbf{x}}_{k-1|k-1} + \underbrace{\mathbf{G}_{k-1}}_{n\times j}\underbrace{\mathbf{u}_{k-1}}_{j\times 1}$$

$$\underbrace{\mathbf{P}_{k|k-1}}_{n\times n} = \underbrace{\mathbf{Q}_{k-1}}_{n\times n} + \mathbf{F}_{k-1}\mathbf{P}_{k-1|k-1}\mathbf{F}^{\mathsf{T}}{}_{k-1}$$

$$\underbrace{\mathbf{K}_k}_{n\times m} = \mathbf{P}_{k|k-1}\underbrace{\mathbf{H}^{\mathsf{T}}}_{n\times m}\underbrace{[\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^{\mathsf{T}} + \mathbf{R}_k]^{-1}}_{m\times m}$$

$$\mathbf{P}_{k|k} = [\mathbf{I} - \mathbf{K}_k\mathbf{H}]\mathbf{P}_{k|k-1}$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k(\underbrace{\mathbf{z}_k}_{m\times 1} - \underbrace{\mathbf{H}}_{m\times n}\hat{\mathbf{x}}_{k|k-1} - \mathbf{H}\mathbf{G}_k\mathbf{u}_{k-1})$$

Ex: Kinematic KF: Tracking

- Consider a System with Constant Acceleration

$$\ddot{y} = -g$$
$$\dot{y} = gt + p_1$$
$$y = p_0 + p_1 t + \frac{gt^2}{2}$$

$$\begin{bmatrix} \dot{y} \\ \ddot{y} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} y \\ \dot{y} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ g \end{bmatrix}$$

$$\mathbf{F} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad \mathbf{F_k} = \begin{bmatrix} 0 & t_s & \frac{t_s{}^2}{2} \\ 0 & 0 & t_s \\ 0 & 0 & 0 \end{bmatrix}$$

$$\hat{\mathbf{x}}_k = \mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1} + \mathbf{K}_k(\mathbf{z}_k - \mathbf{H}\mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1})$$

In Summary

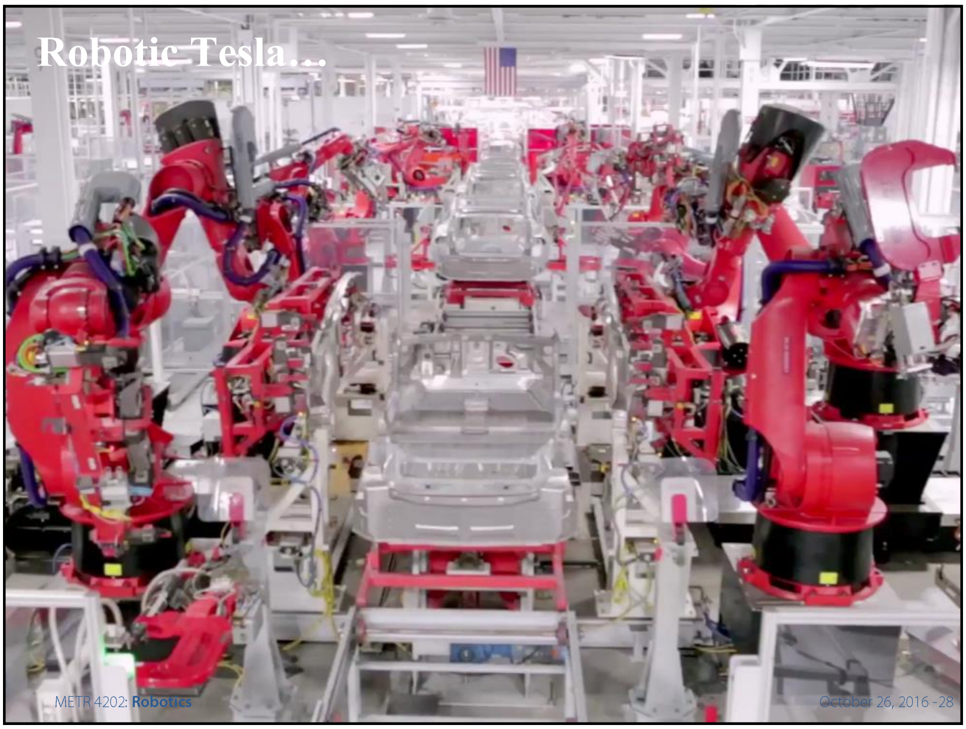
- KF:
  - The true state (*x*) is separate from the measured (*z*)
  - Lets you **combine** prior controls knowledge with measurements to filter signals and find the truth
  - It **regulates** the covariance (P)
    - As P is the scatter between *z* and *x*
    - So, if P → 0, then *z* → *x* (measurements → truth)
- EKF:
  - Takes a Taylor series approximation to get a local “F” (and “G” and “H”)

Future of Robotics

(Self-Driving Vehicles)

(Notes from Prof. John Leonard, MIT)

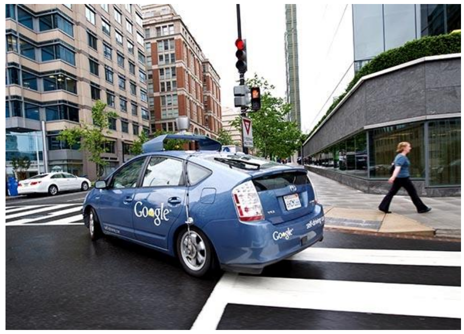
Robotic Tesla…



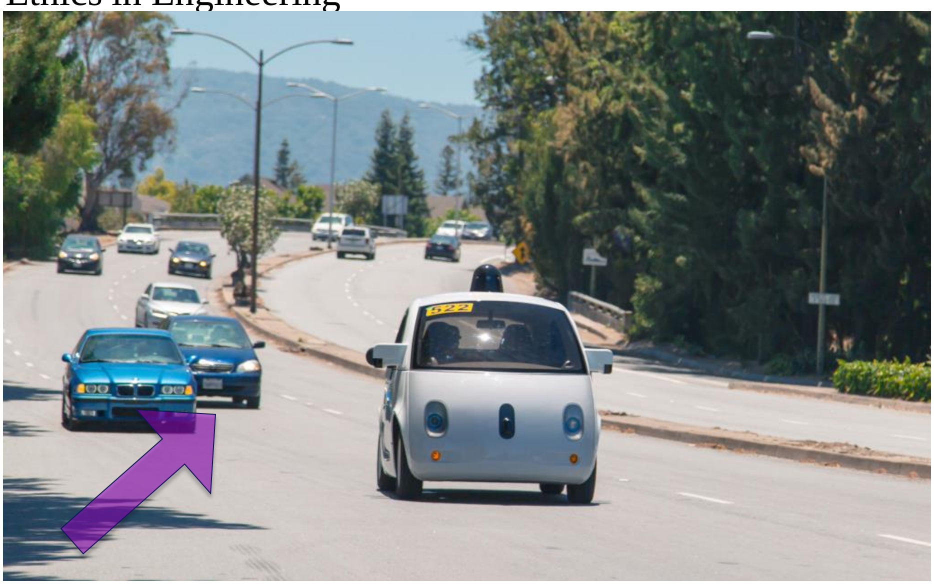
Other Robotic Tesla…

Cars: Software/Robots With 4 Wheels

Robotics & Automation Has Limits Too



More to Dynamic “Obstacles” than one’s own Control… Ethics in Engineering



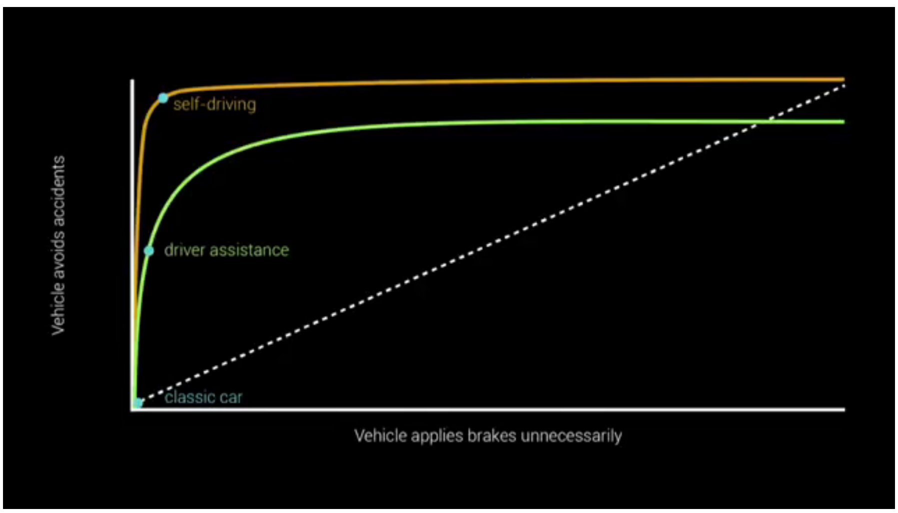
Q: Why has Google has chosen to exclusively pursue level 4?

A: They don't trust people to pay attention

t=41.56: "people do really stupid stuff when they are driving...it isn't pretty. The assumption that humans can be a reliable backup for the system was a total fallacy.   Once people trust the system, they trust it"

Astro Teller, Head of GoogleX, March 2015

"Vehicle Avoids Accidents" vs. "Vehicles Applies Breaks Unnecessarily"



Chris Urmson Keynote Address at the Intelligent Transportation Systems 25th Annual Meeting & Expo, Pittsburgh, May 2015

THE WALL STREET JOURNAL.

Google Brings in Chief for Self-Driving Cars

Hiring of Detroit veteran John Krafcik indicates keenness to commercialize the technology

Google has hired Detroit veteran John Krafcik to run its self-driving car division, sending a message that it is serious about the commercial viability of the autonomous vehicles business. Photo: Zuma Press

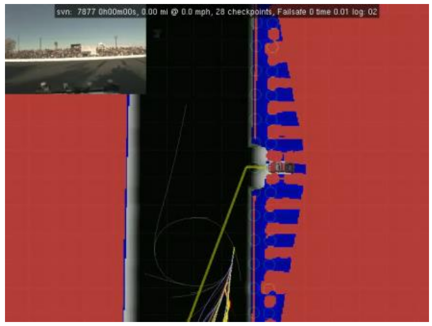
By ALISTAIR BARR And MIKE RAMSEY

49 COMMENTS

2015 11:04 p.m. ET

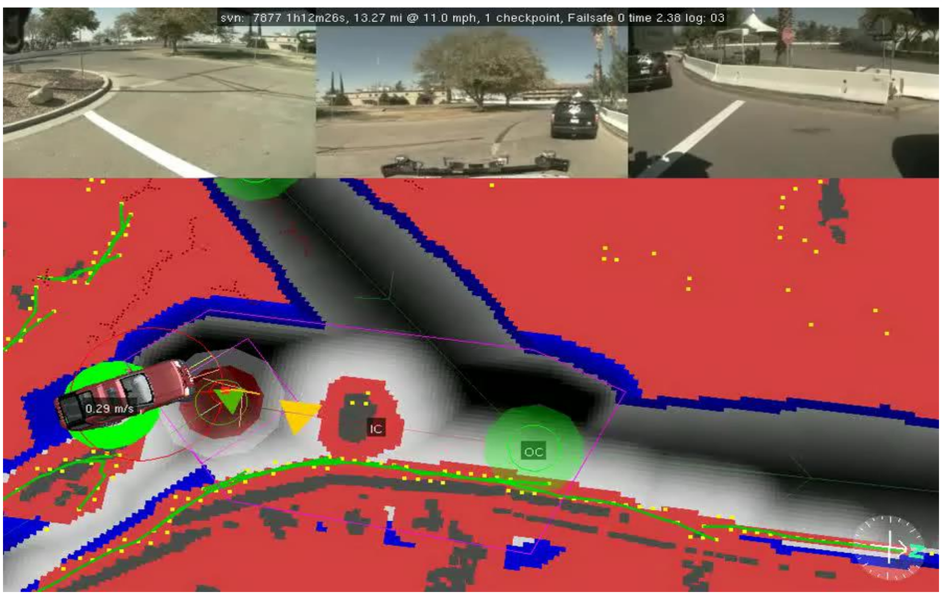
"When the company wanted a team of roboticists, it raided a University Lab to get them. Can high-tech academia survive today's Silicon Valley talent binge?"

MIT DARPA Urban Challenge Team (2006-2007)



Leonard et al., JFR 2008 ; Karaman and Frazzoli, IJRR 2011; Huang et al., AR 2009

2007 DARPA Urban Challenge – Collision between MIT and Cornell



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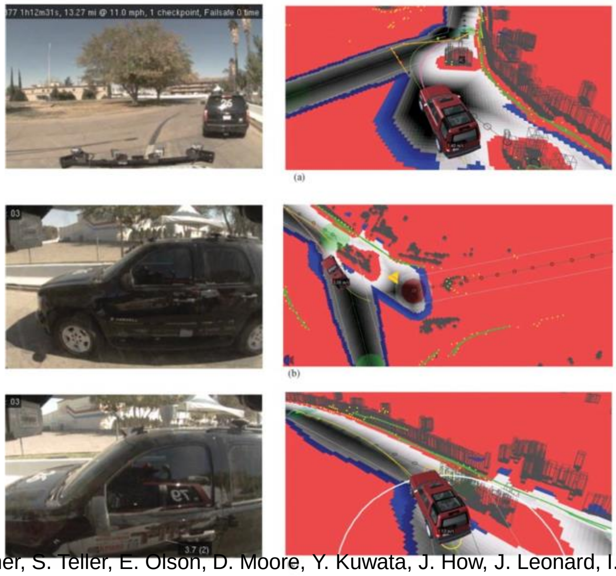


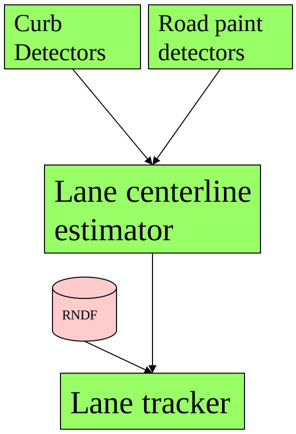
L. Fletcher, S. Teller, E. Olson, D. Moore, Y. Kuwata, J. How, J. Leonard, I. Miller, M. Campbell, D. Huttenlocher, and others, "The MIT–Cornell collision and why it happened." In Journal of Field Robotics, 25(10), pages 775-807. 2008.

From Prof. Ed Olson (Umich): The logic of whether to represent an "obstacle" as a track (i.e., something with velocity) or as a blob, was this (relevant part is highlighted):

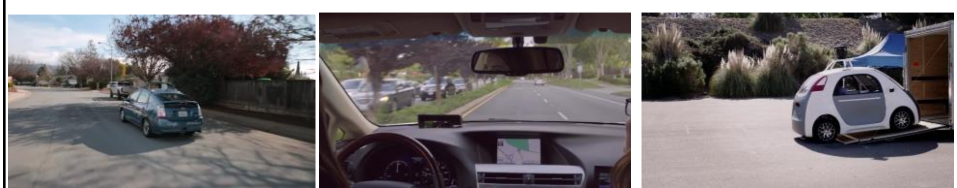
```
int use_track = 0, use_rects = 1;
//        if (t->vmag > 4)
//            use_rects = 0;

    if (t->vmag > 3.0 && t->maturity > 8)
            use_track = 1;
    double MAX_DIM = 10;
    if (t->box.size[0] > MAX_DIM || t->box.size[1] > MAX_DIM)
            use_track = 0;
```

Lane Estimation (PhD Thesis of Albert Huang, supervised by Prof. Seth Teller)

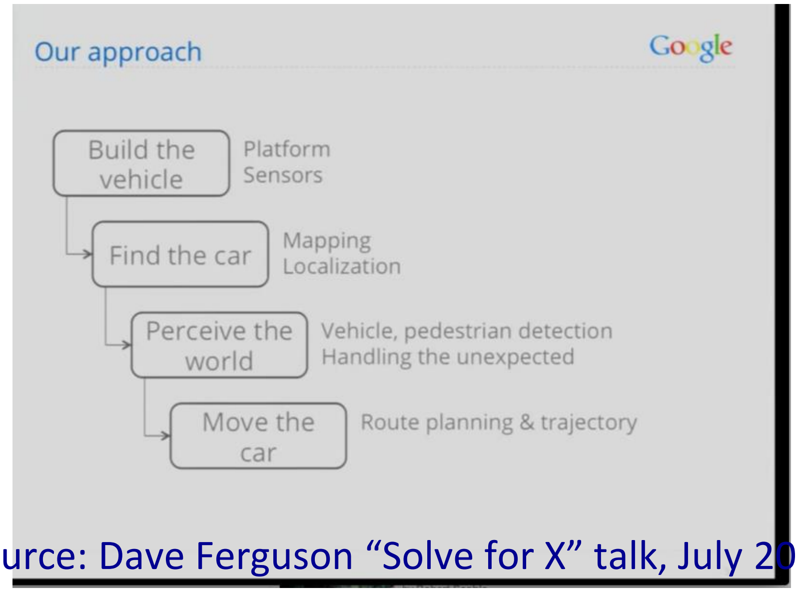


2015: Self-Driving Vehicles Have a Perception Problem



- The Google Car is an amazing research project that might one day transform mobility
- The technology of the Google Car, however, has been over-hyped and is poorly misunderstood
- This has led many people to say that self-driving is a "solved" problem
- "Just because it works for Google", doesn't mean it will work for everyone else

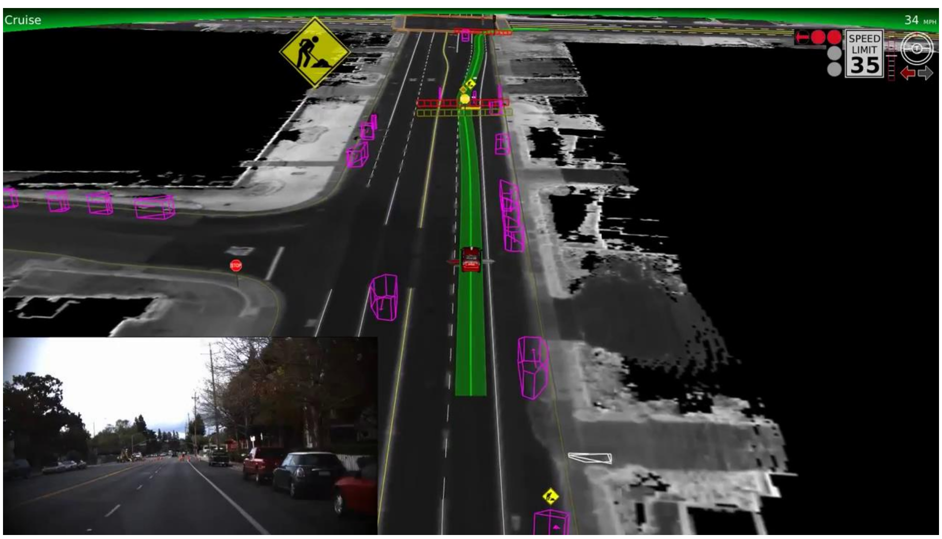
How Does Google's Self Driving Car Work?



Source: Dave Ferguson "Solve for X" talk, July 2013

http://www.youtube.com/watch?v=KA_C6OpL_Ao

Google: Lidar Localization with an a priori map



https://plus.google.com/+GoogleSelfDrivingCars/videos

SDVs: The Big Questions Going Forward

- Technical Challenges:
- Maintaining Maps
- Adverse Weather
- Interacting with People
- Robust Computer Vision (towards PD=1.0, PFA = 0.0)?

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- Can humans be trusted to take control when necessary?

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- Can humans be trusted to take control when necessary?
- The big question for Level 4 approaches? (i.e., Urmson)
- Can near-perfect ROC curves be obtained in a wide variety of demanding settings?

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- Maintaining Maps
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- Interacting with People
- Robust Computer Vision (towards PD=1.0, PFA = 0.0)?
- The big question for Level 3 approaches? (i.e., Musk)
- Can humans be trusted to take control when necessary?
- The big question for Level 4 approaches? (i.e., Urmson)
- Can near-perfect ROC curves be obtained in a wide variety of demanding settings?
- Level 2.99 – Hidden Autonomy (Human must pay attention, but autonomy will jump in to prevent accidents)

Summary – Self-Driving Vehicles

- Transformative technology that can/will change the world, but many open questions
- Hope for reducing accidents and saving lives
- Admiration for Google's audacious vision and amazing progress
- Impressed by recent efforts by auto manufacturers
- Pride for the robotics community's contributions
- Fear that the technology is being over-hyped
- Uncertainty about open technological challenges, such as:
  - left-turn across high-speed traffic onto busy roads
  - Interpretation of gestures by traffic cops, crossing guards etc
  - Effect of changes in road surface appearance on map-based localization
  - Capability to "predict what will happen next" in demanding situations
  - Operations in adverse weather

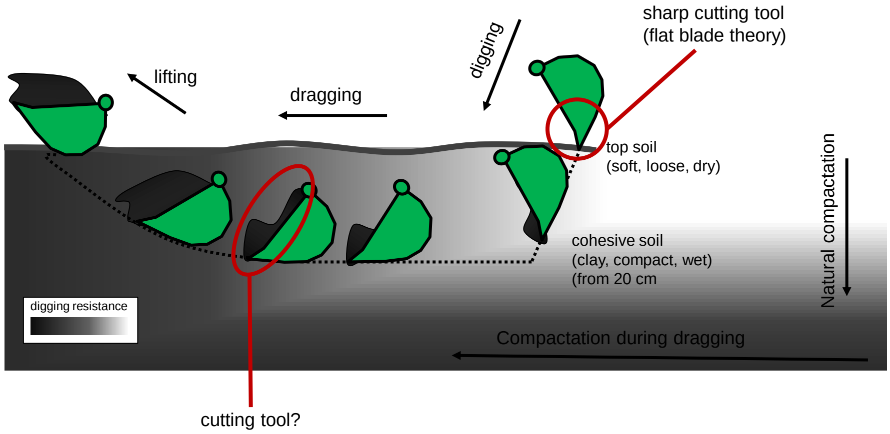
Future of Robotics

Move Heaven & Earth

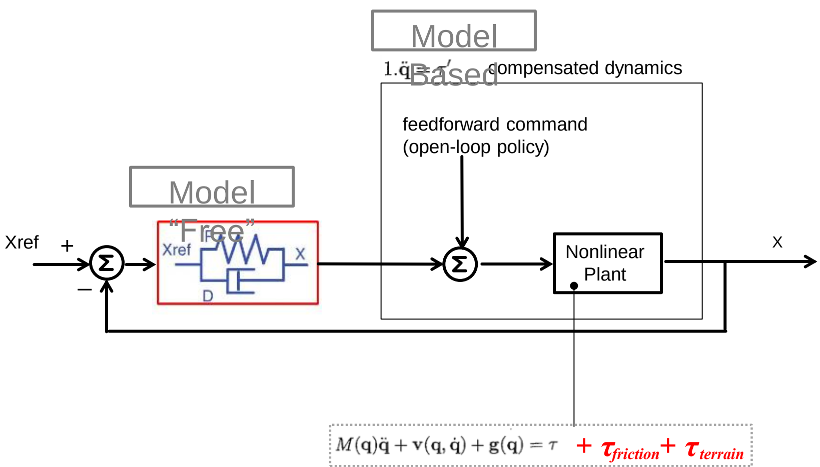
“Field Arm” Motion Generation

Terrain is Not “Structured,” But It’s Not Random…

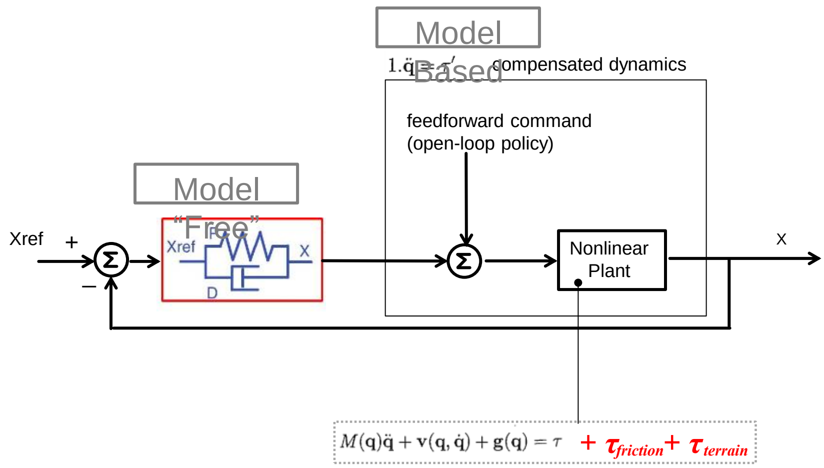
Excavation as Terrain Manipulation



Operation Space (Computed Torque) (2 DOF Example)

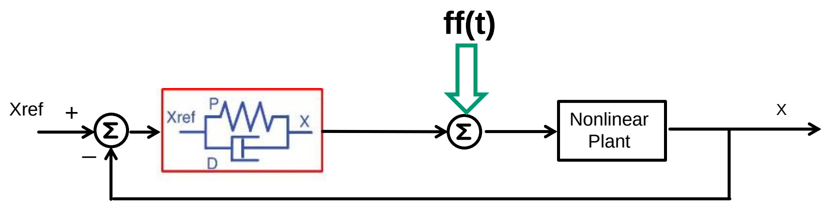


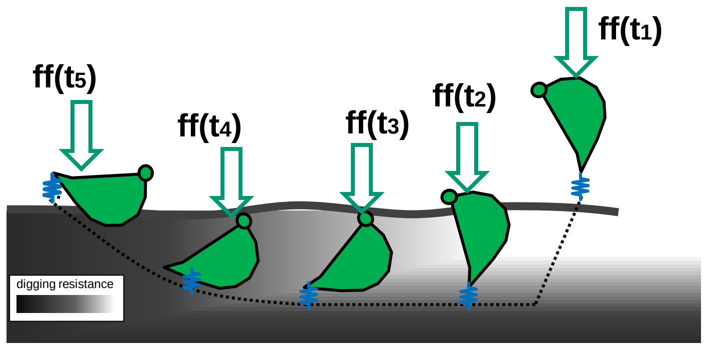
Operation Space (Computed Torque) (2 DOF Example)



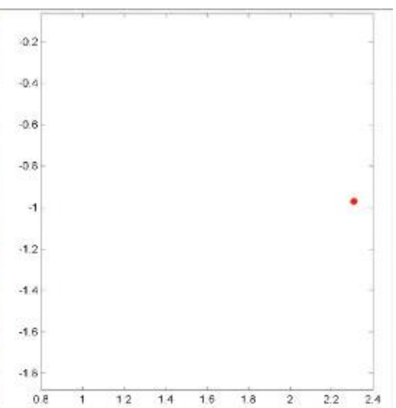
Reminder: Compensated Manipulation

Thus for Excavation …



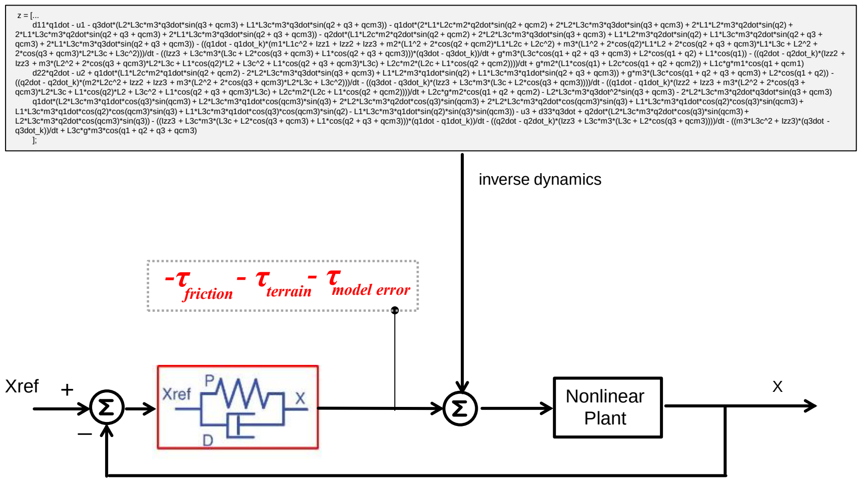


Manipulation under Large Disturbances

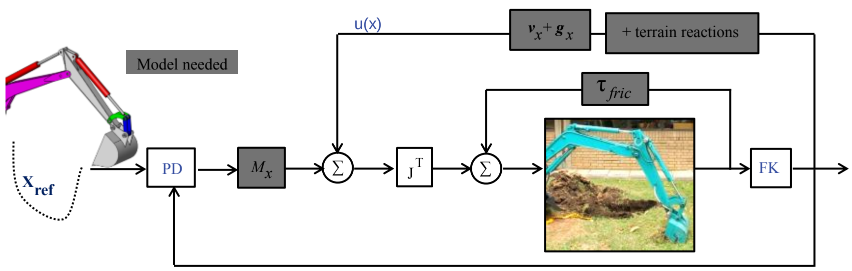


Inverse Dynamics is Not Trivial

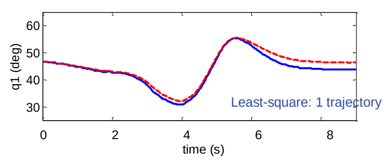
Inverse dynamics helps, but performance is dependent on model structure and parameter identification



Local Compensation

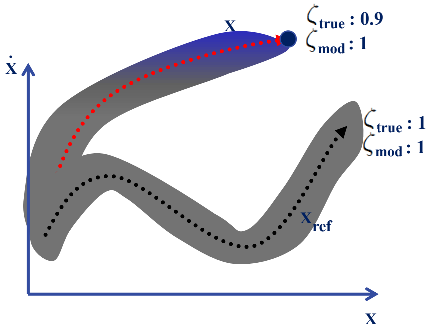


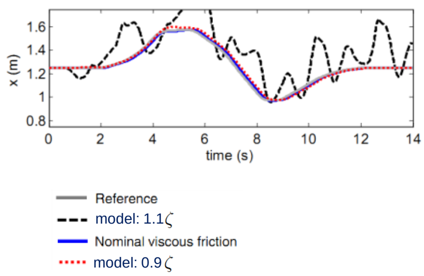
- Modelling globally is hard
- Local models are easy, but can destabalize



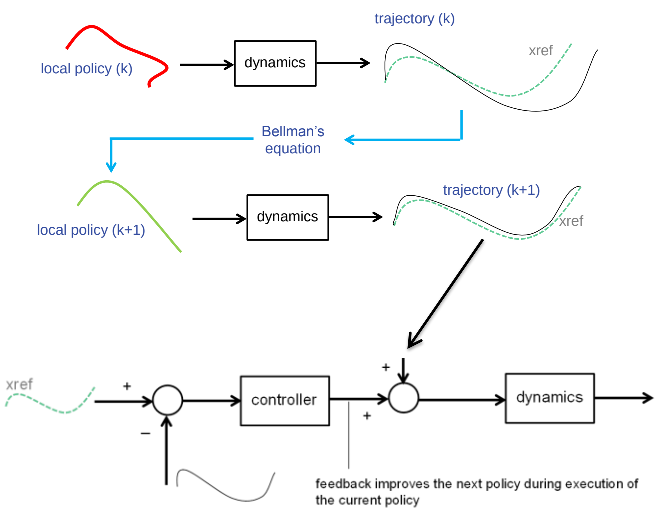
Local model + Disturbance = Wrong Compensation

- Unless tracking is perfect, a state that is far from $\mathbf{x}_{\mathbf{ref}}$ will require a different model





Model Updating & Iterative Tracking…



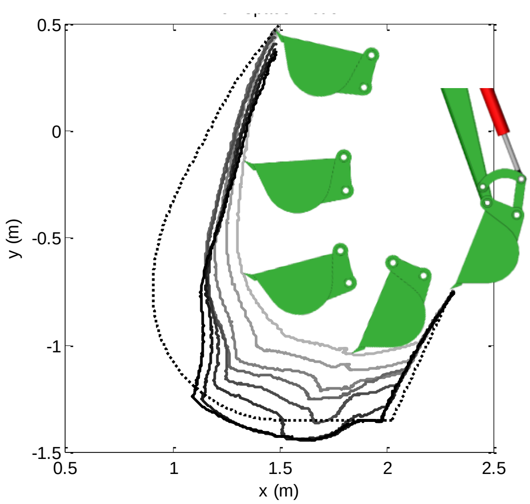
Pay Dirt!

Clay friction

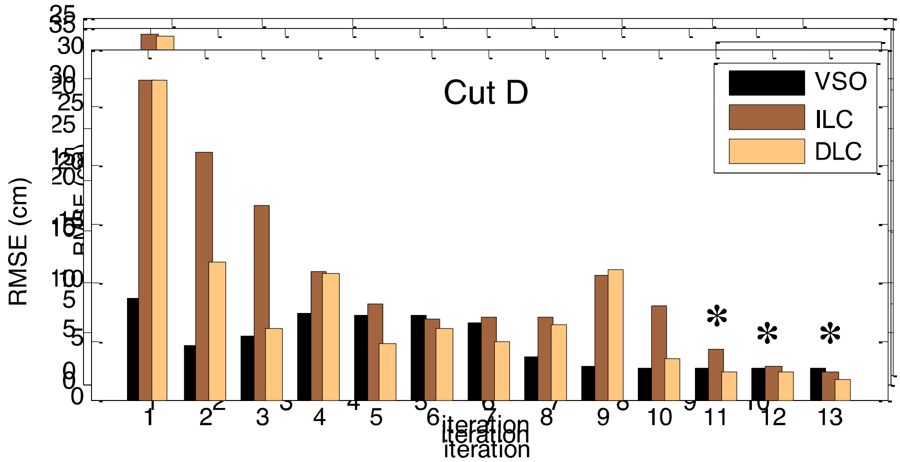
Broken red bricks

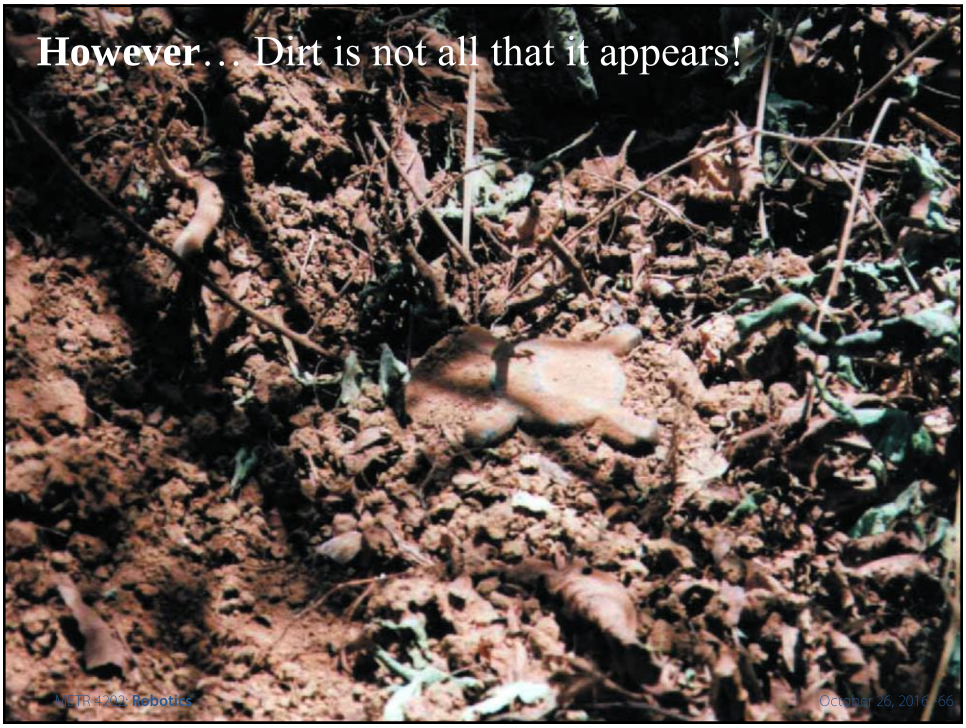
Clay friction

Pay Dirt:
Looking at Trajectories



Pay Dirt:
Looking at Trajectories





Future of Robotics

Medical Robotics

Conclusion and Future Research Challenges

"Soft" robots yield "hard" problems

Goals:

- My dream is to achieve dynamic motion, **particularly of compliant systems under feedback**.
- To *adapt* & *learn* in highly dynamic environments
- Can we robustly integrate continuous planning/control with continuum mechanics to extend our reach

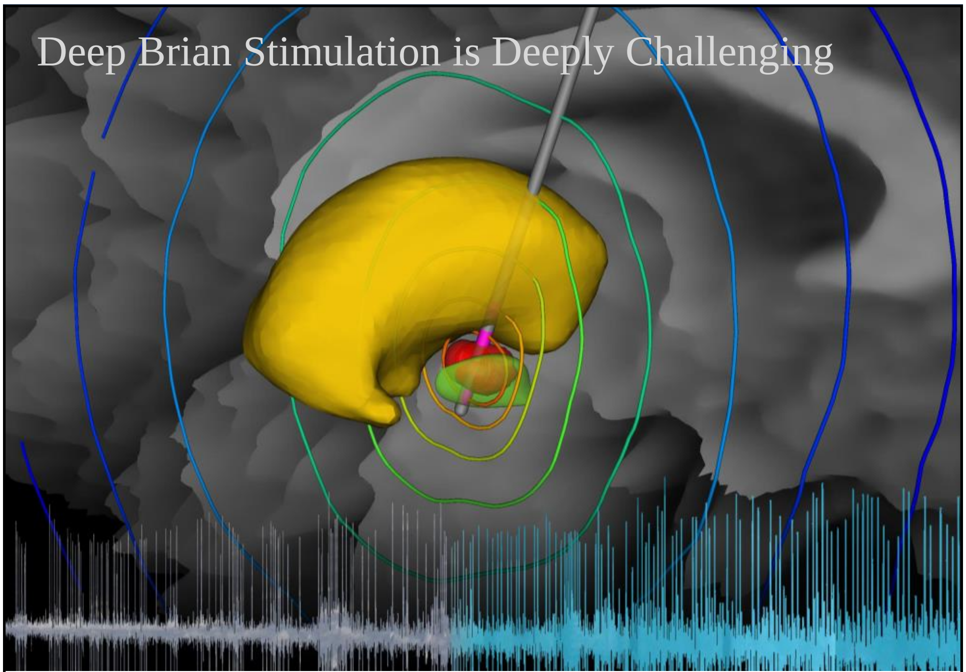
Open Questions:

- Robustness – we would love to have guarantees of performance, but we do not have them for most approaches
- Representation – how can we integrate many different types?
- We need dynamic understanding and robust control (recent work in computer vision/machine learning is exciting, but current precision-recall curves indicate we have a long way to go)

Clinically-motivated applications:

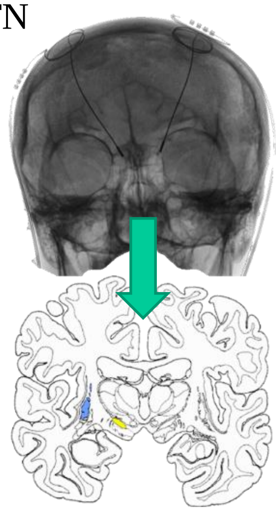
- **Surgical robotics** and **guided therapeutic techniques**

Deep Brian Stimulation is Deeply Challenging

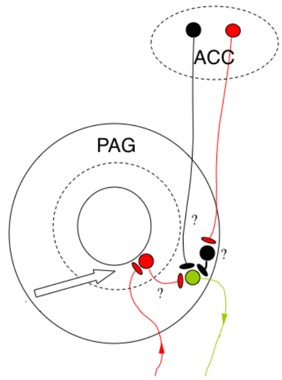


Accuracy is *sine qua non*

- STN



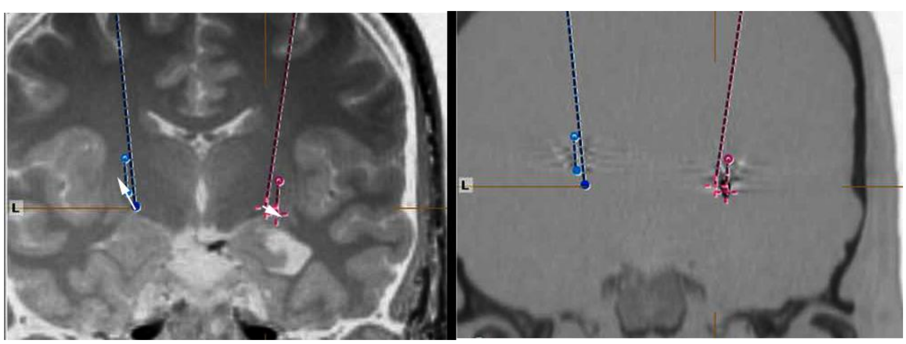
- PAG



Source: Nauta, Feirtag, and Donner, *Fundamental Neuroanatomy*, Freeman, 1986

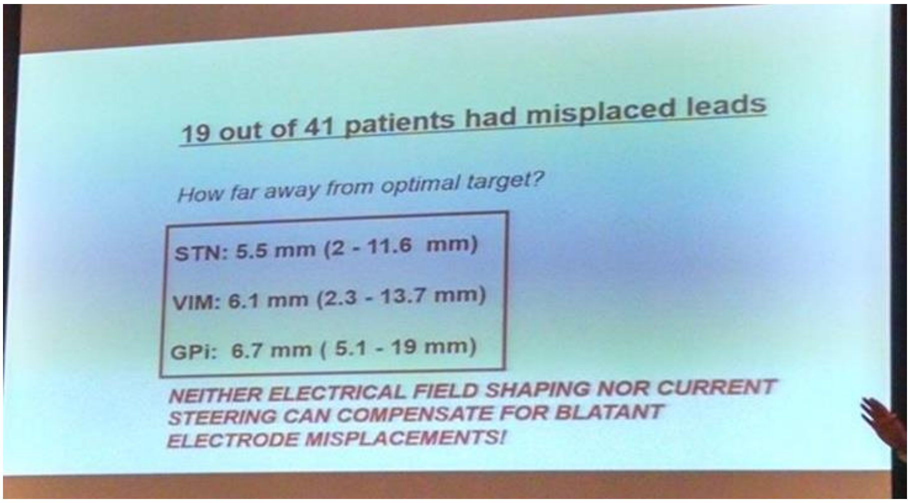
Accuracy is *sine qua non*

- Accuracy of Frame Based Stereotactic Placement via CT/MRI Comparison

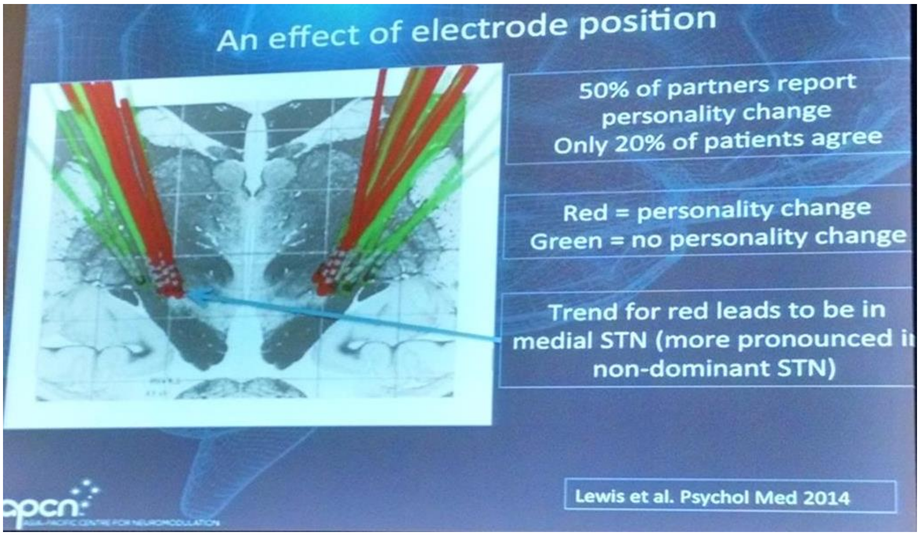


Source: Holloway, Docef, *Neurosurgery* 72[ONS Suppl 1]:ons47–ons57, 2013

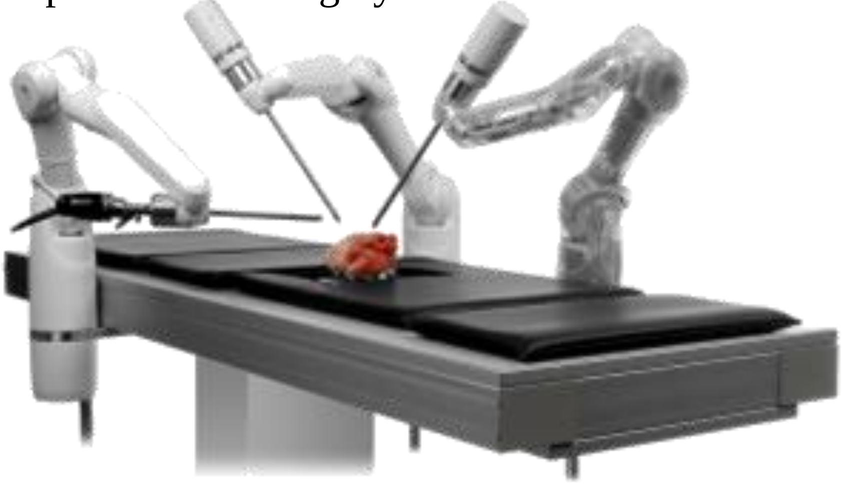
DBS Targeting is Hard



It has consequences…

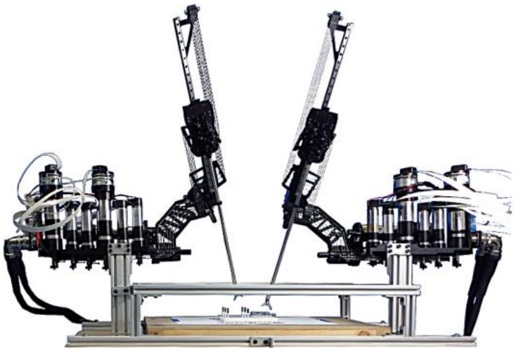


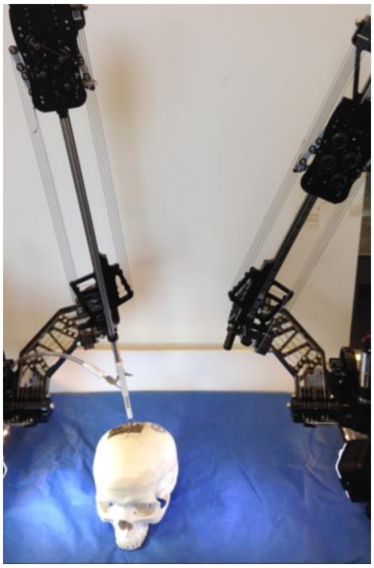
Computer Aided Surgery: Lots of Potential



- Unstructured environment (patient tissue) makes this harder

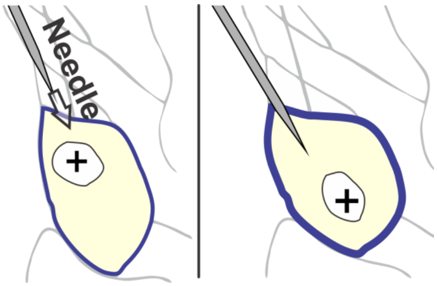
Neurosurgical Robotics

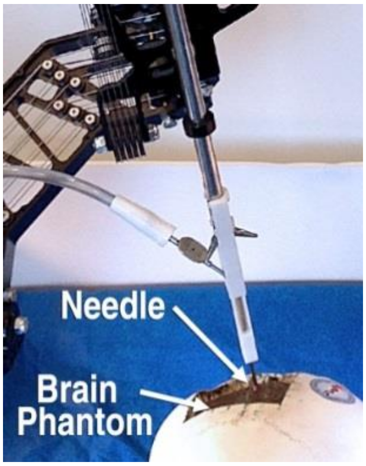




Neurosurgical Robotics:

- **Biomechanics approach**:
  Predict expected tissue trajectories





ARC DP160100714

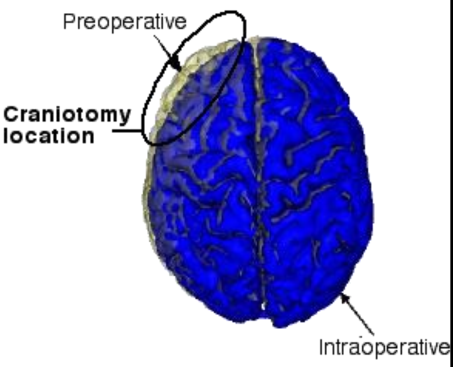
“**Soft**” is “**Hard**” (but not impossible)

S. List, UWA

→ Many Issues: Including Craniotomy Induced Brain Shift

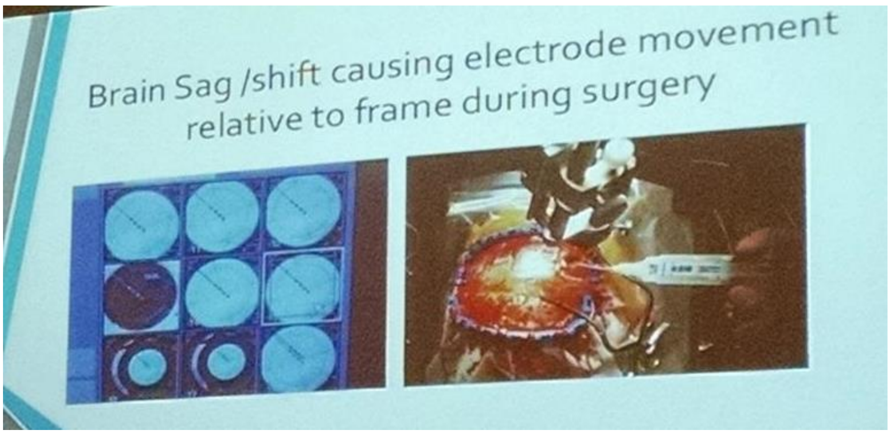
Soft Tissue Mechanics: Brain Shift/Brain Sag

Ex: Image-guided neurosurgery

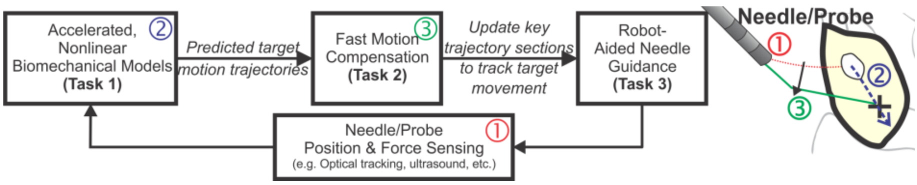


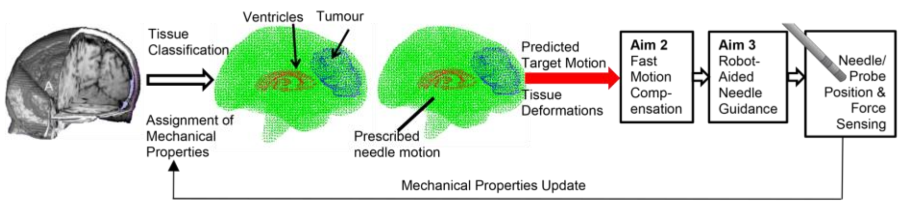
Courtesy: SPL, Harvard

Brain Shift Identified in Neurosurgery Community



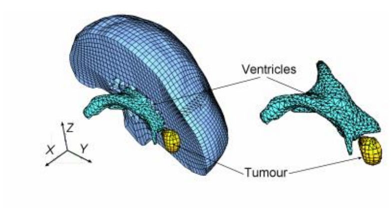
A Robotic “Plan”: Handling Brian Shift

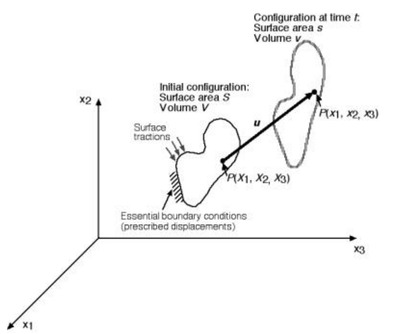




Treating Brain Shift Mechanically

- Post this as a Biomechanics Problem
- Non-linear Continuum Mechanics Problem





$$\int_V \tau_{ij} \delta \varepsilon_{ij} dV = \int_V f_i^B \delta u_i dV + \int_S f_i^S \delta u_i dS$$

Qualitative Evaluation – Canny Edges

Biomechanics

BSpline

Red contours – Intra-operative

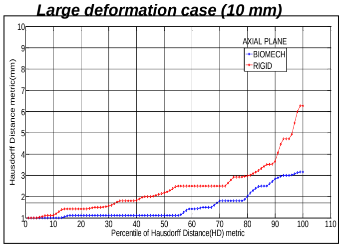
Blue contours – Warped pre-operative

Green contours – Overlap

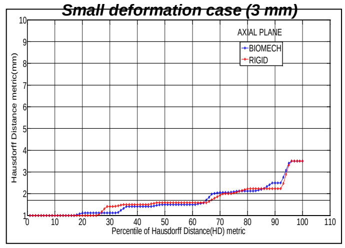
Mostayed et al. (2013) *Annals of Biomed. Eng.* 41(11), 2409-2425

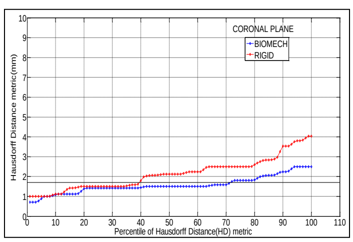
Comparison:Hausdorff Distance Metric

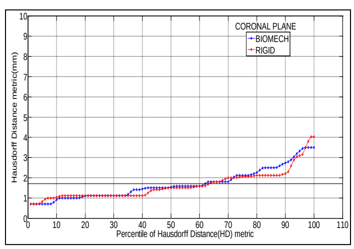
Large deformation case (10 mm)



Small deformation case (3 mm)

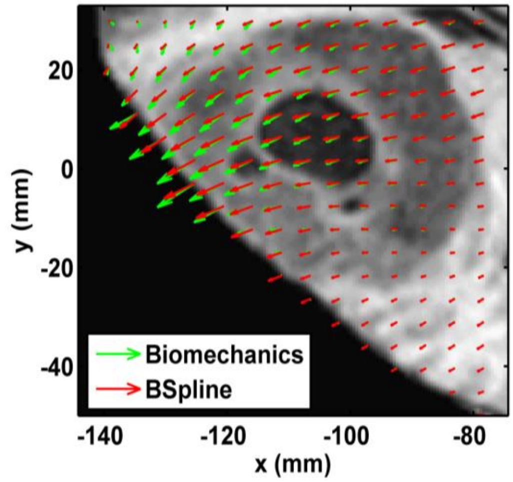






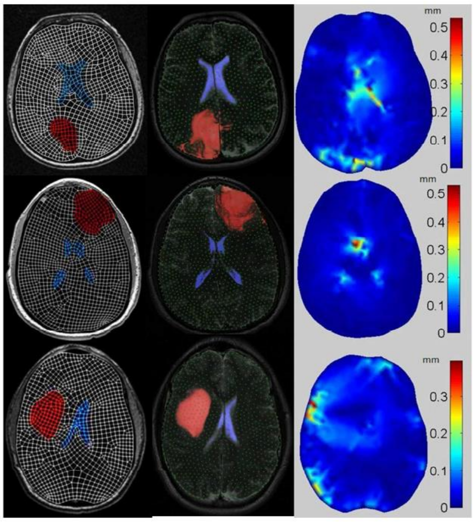
- Comparison of Biomechanics-based & rigid registrations

Qualitative Evaluation: Deformation Field



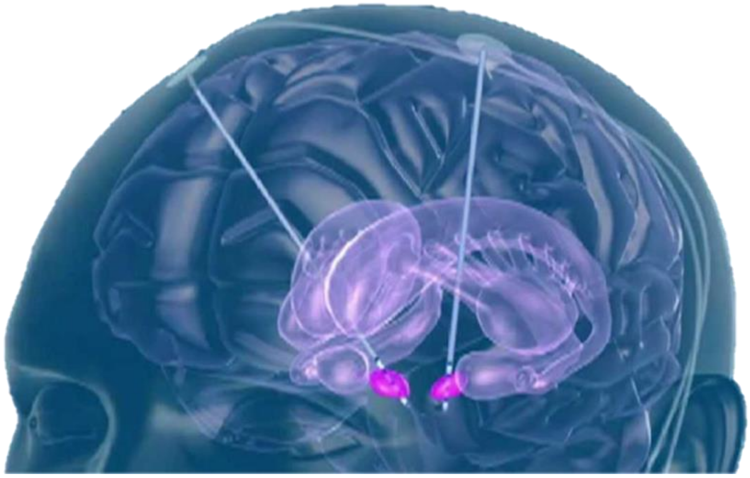
Mostayed et al. (2013) Biomechanical Model as a Registration Tool for Image-Guided Neurosurgery: Evaluation Against BSpline Registration. *Annals of Biomedical Engineering. 41(11), 2409-2425*

Accuracy for Mesh-free Models

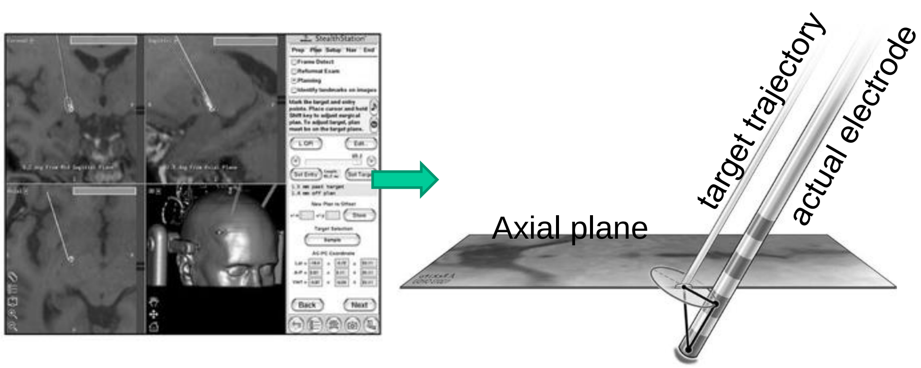


***Left*: Finite Element Models** ***Middle*: Fuzzy Mesh-free Model** ***Right* : Difference of the simulation results**

Targeting:
We Already Do Careful Preoperative Planning



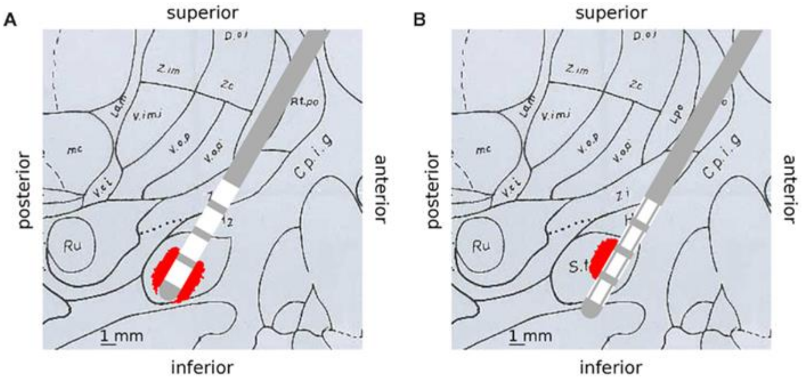
The Best Laid Plans …



Source: Burchiel, McCartney, *et al.*, *J Neurosurg* **119**:301–306, 2013

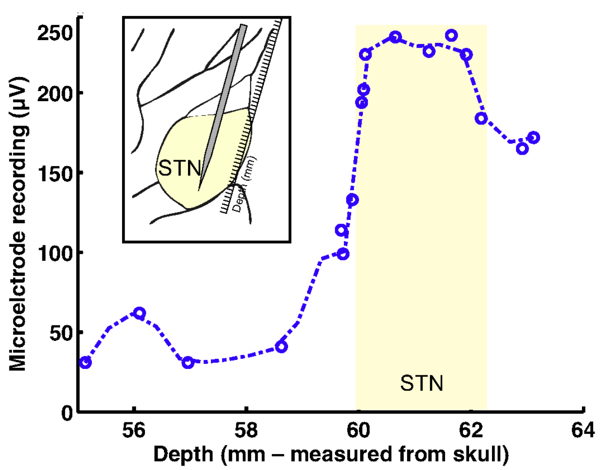
Does This Suggest Steering/Path Correction?

- Plan:
- Result:

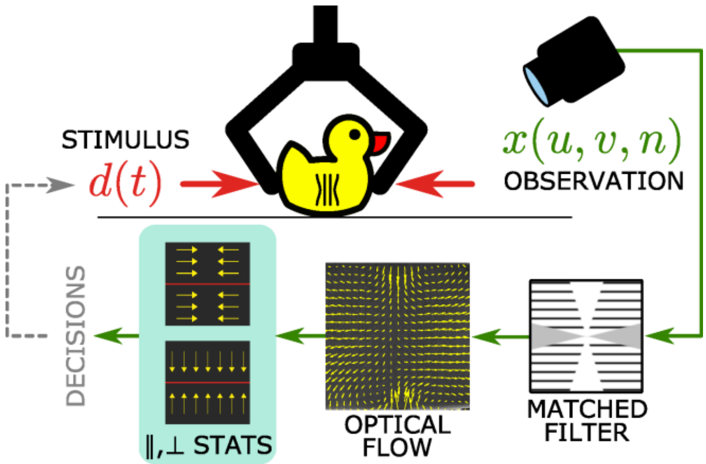


- Stereotactic (Leksell) frames alone are not enough…
- Brain Shift, Compliance, Drift, etc.

In-Vivo Feedback: Incorporating MER
Incorporating tissue signal signatures

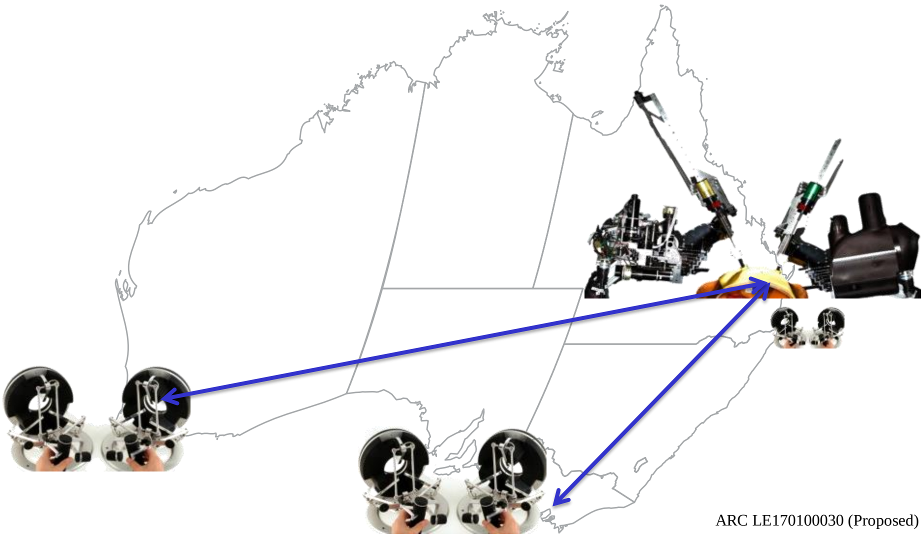


What's Next? Incorporating Stiffness: Visual Deformable Object Analysis



Dansereau, Singh, Leitner, *ICRA 2016*

What's Next: Open Access Robotics Infrastructure for High-Fidelity Telesurgical Research

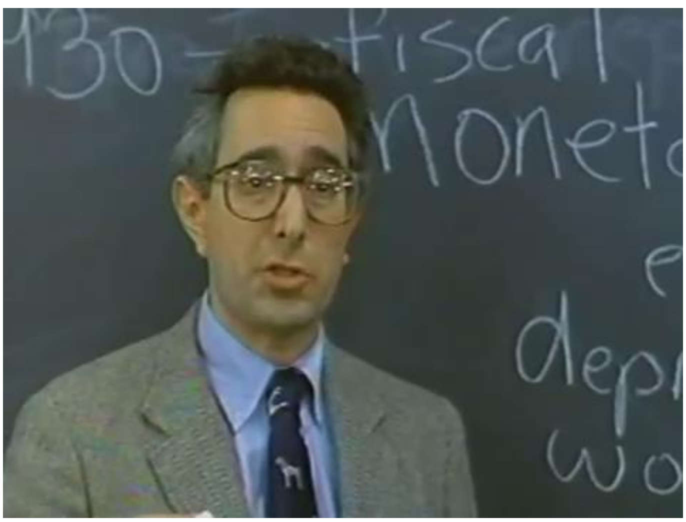


ARC LE170100030 (Proposed)

SECaT Time! … Brought To You By the Number 5

"4" Is Average

- What is a 3?



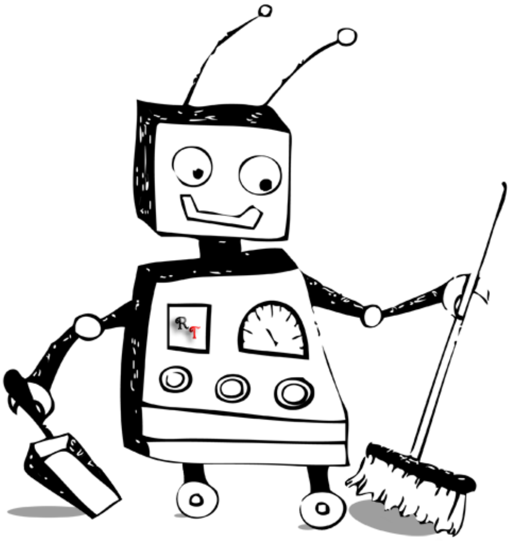
SECaTs: Some Lessons in the Works for Next Year

- I shall only use my own slides
- Less is more!
  - Smaller assignments
  - More time for Examples
- Better organization
  - Better tutorials
  - More examples!!
  - I get that. But, we've come a long way

➔ To make this happen I need your support!

Now Finally Some Philosophy (I am a Dr of it!!!)
Systems: Signals, Controls…A Fundamental Yearn!

© National Geographic. Mount Everest at night
(the lights along the apex are the headlamps of other mountaineers)



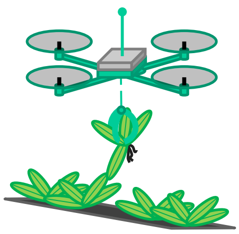
UQ Robotics: Dynamic Systems in Motion

Diverse international research group

Hanna Kurniwati
(NUS/MIT)
Paul Pounds
(ANU/Yale)
Surya Singh
(Stanford/Syd)

Planning

Aerial Systems



Bio-inspired Systems

Mechanics of motion