Human Motor Performance in Robot-Assisted Surgery

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Robotics for Medical Interventions

Rehabilitation

Prosthetics

Robot-assisted surgery

Robot-Assisted Minimally Invasive Surgery

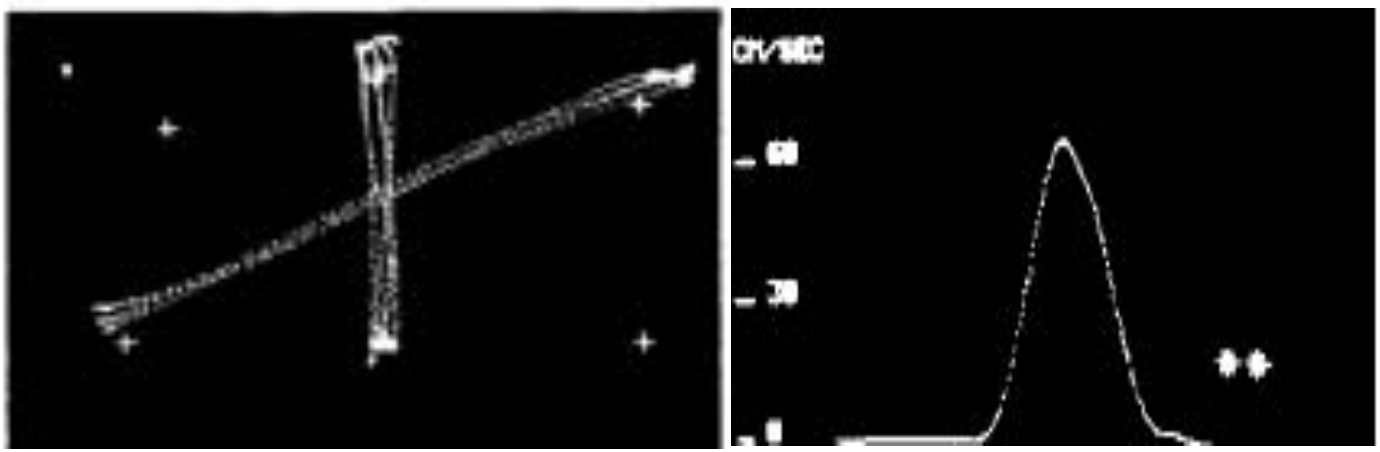
- Design does not fully consider the sensorimotor capabilities of the surgeon
- Training methods have not been optimized

Studying the sensorimotor system could impact both!

Computational Motor Control

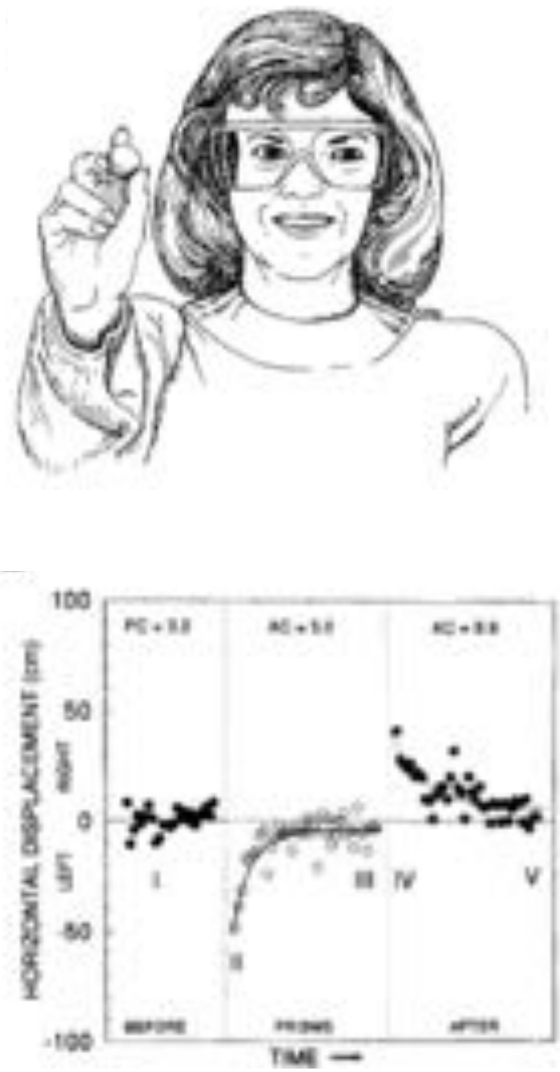
The science of how the brain controls motion and represents the external world

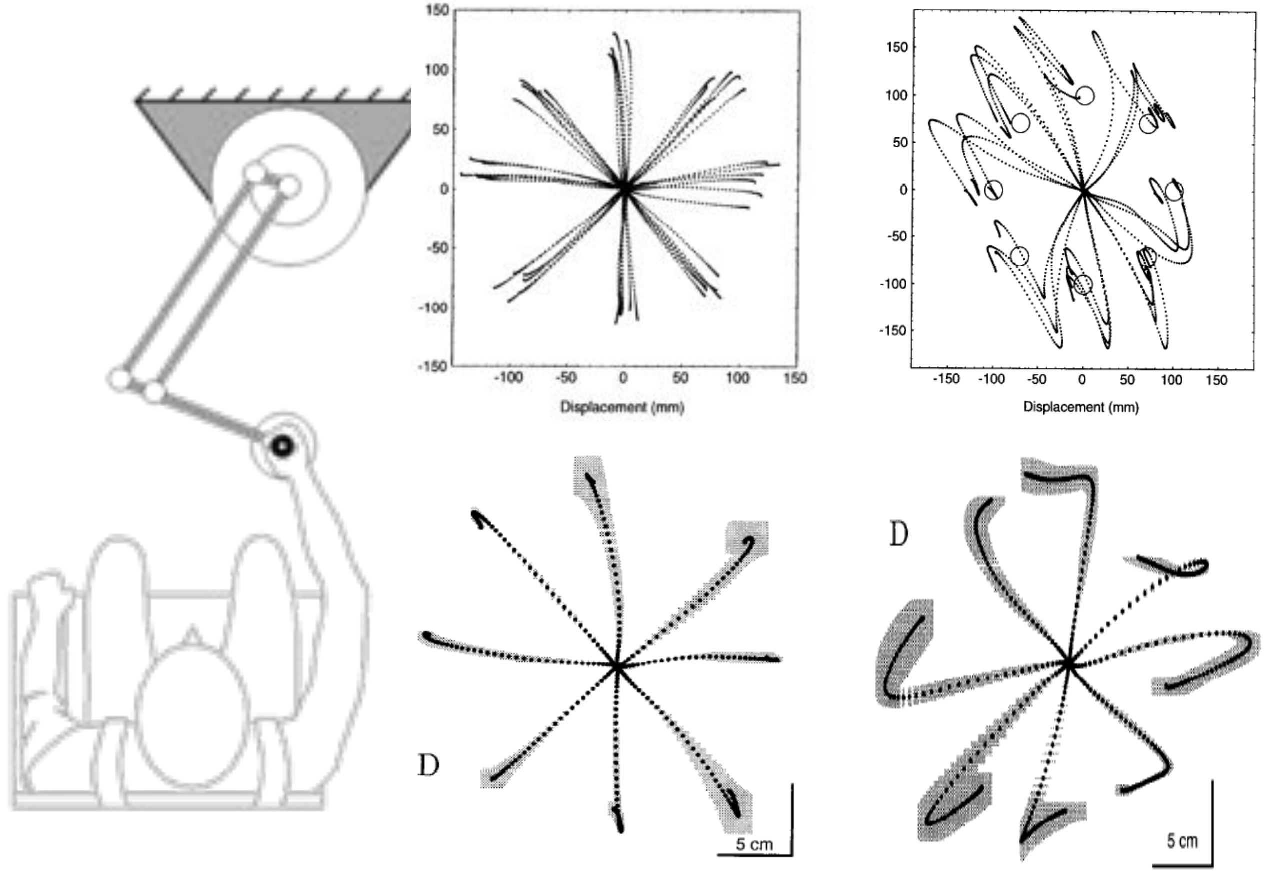
We move in surprisingly regular ways…



Morasso, 1981

Adaptation to Perturbations





Martin et al., 1996

Shadmehr and Mussa-Ivaldi, 1994

Take Home

To build robotic systems that are operated by **humans**, we should:

- Study the **human operator**
- Apply findings to design, control, and training

Operators interact with robotic devices

- This allows us to study the **human operator** in unprecedented ways

Surgery

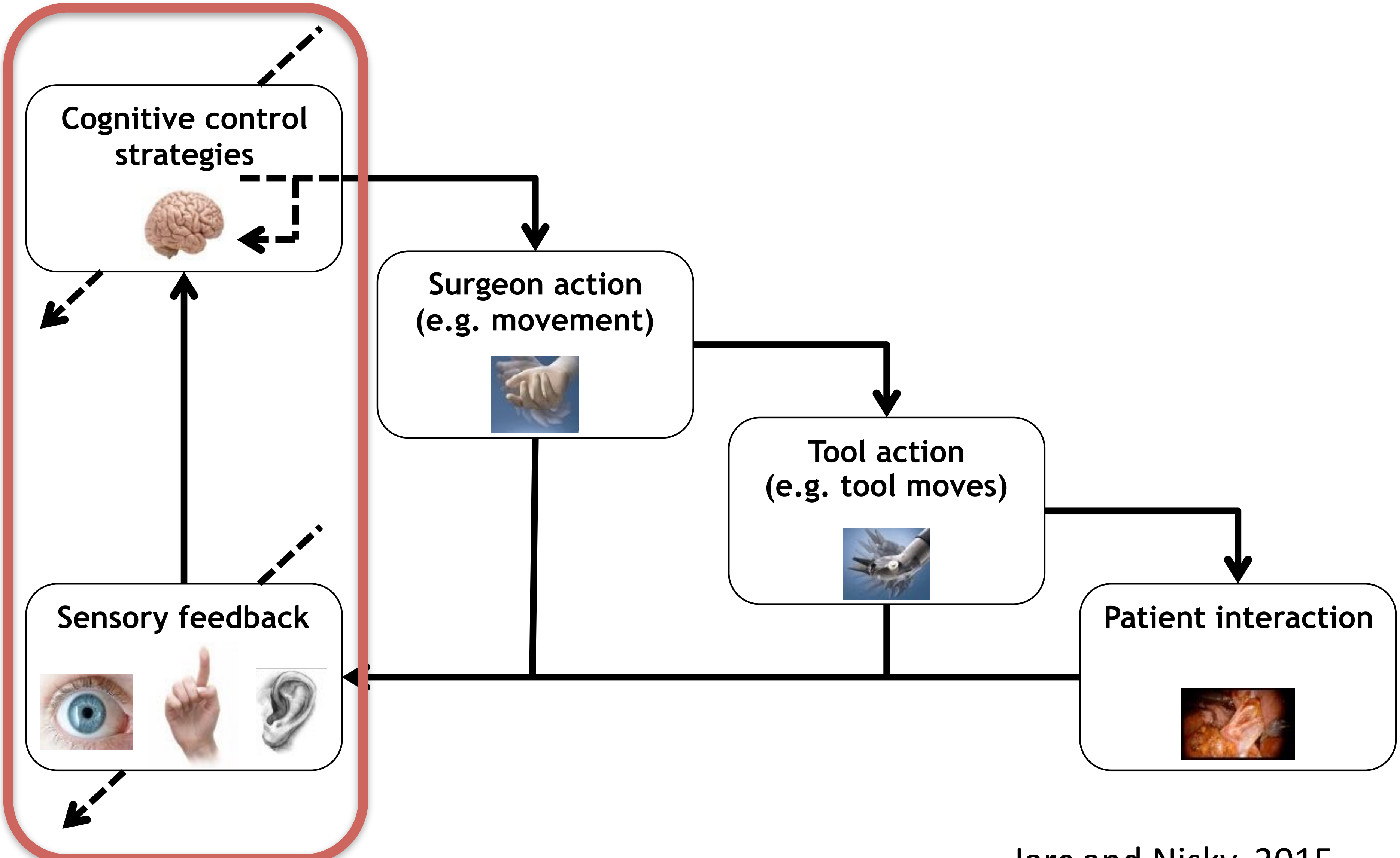
Open

Minimally Invasive

Robot-Assisted

Intuitive Surgical

Sensorimotor Performance in RAS



Jarc and Nisky, 2015

Sensorimotor Performance in RAS

Can we use (and extend) what we know about

human motor control

to improve

design, control, and training

in

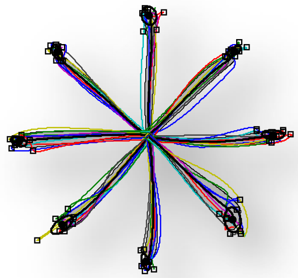
Robot-Assisted Surgery?

Sensorimotor Performance in RAS

Compare teleoperated vs. freehand movements, and expert vs. novice participants

- Teleoperation vs. freehand => robot design
- Experts vs. novices => skill evaluation and training

(1) Tool-tip kinematics

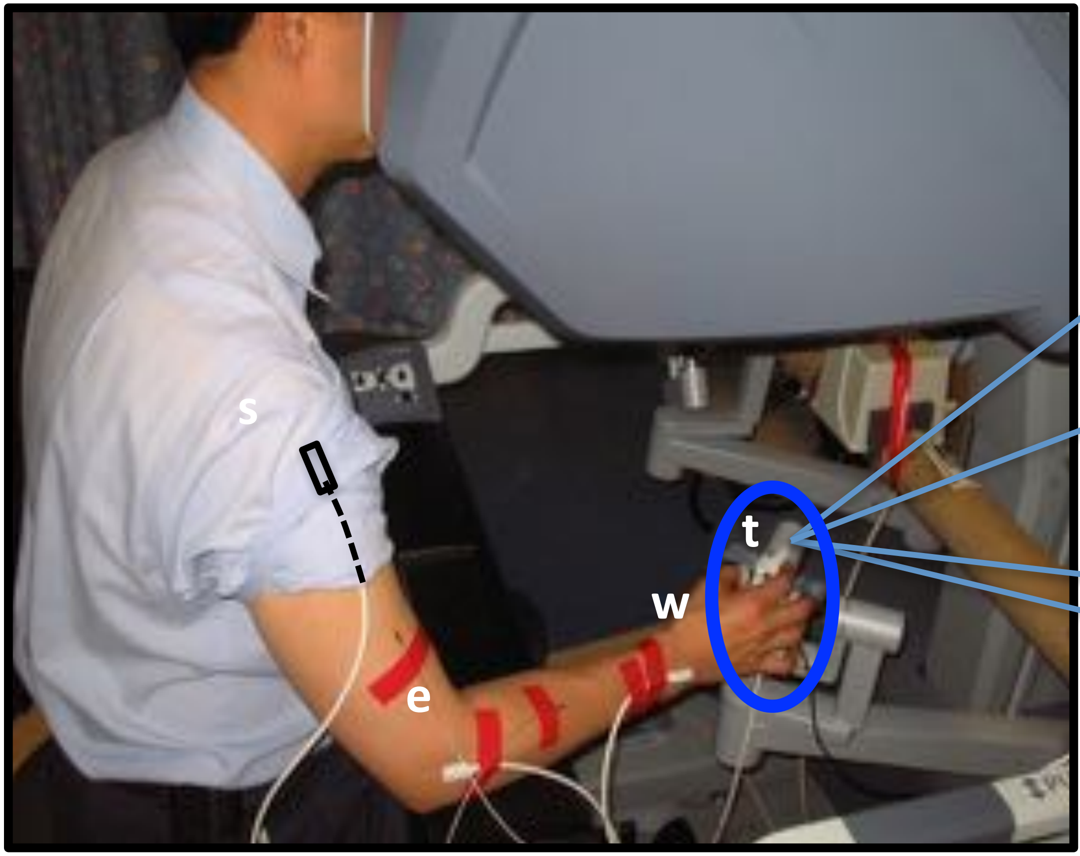


(2) Arm posture variability

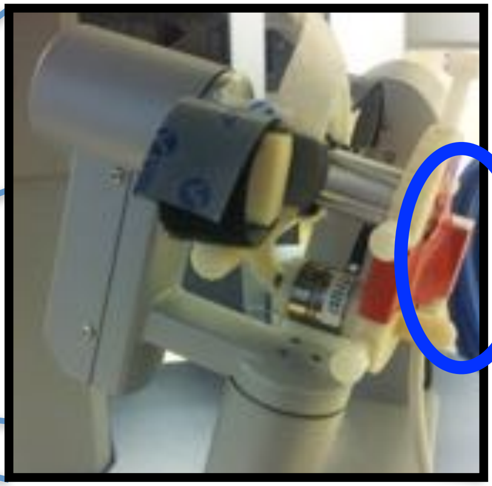
Experimental Setup

Experimental Setup

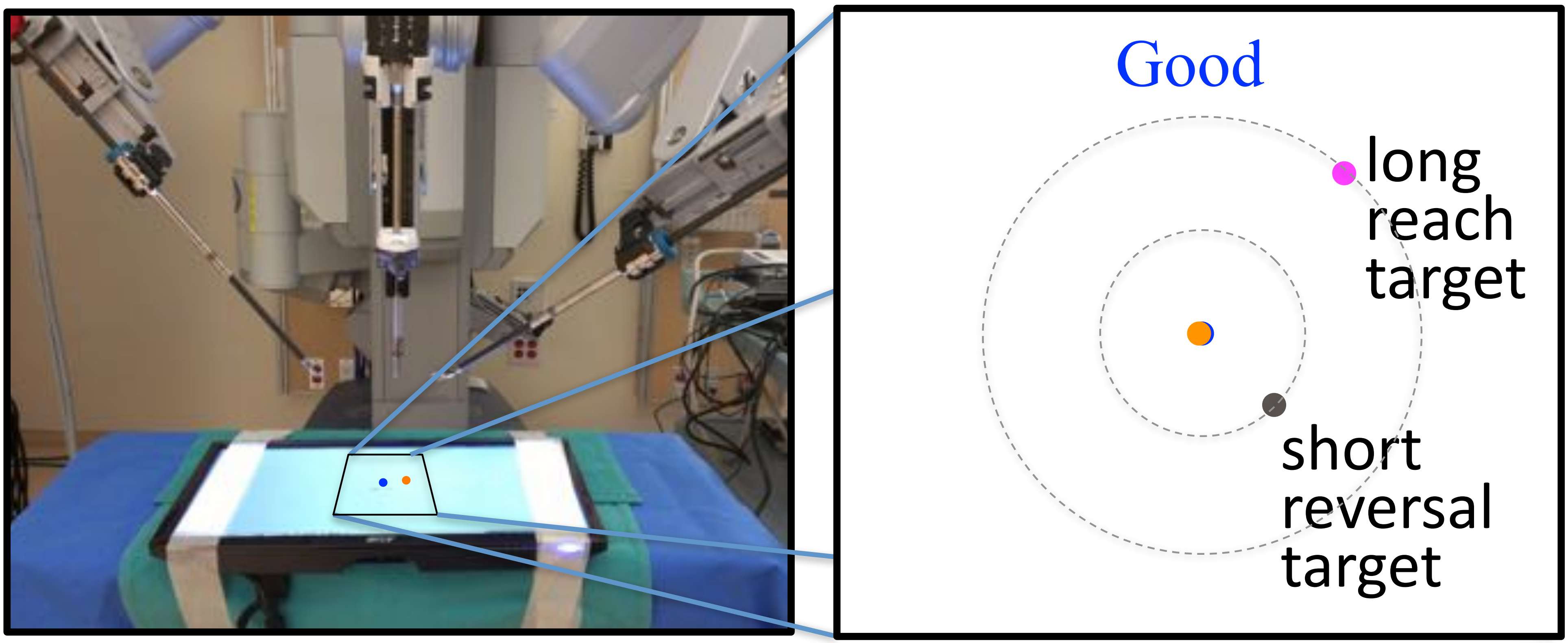
Pose trackers on user arm



Grasp fixture – position and force sensing at tool tip



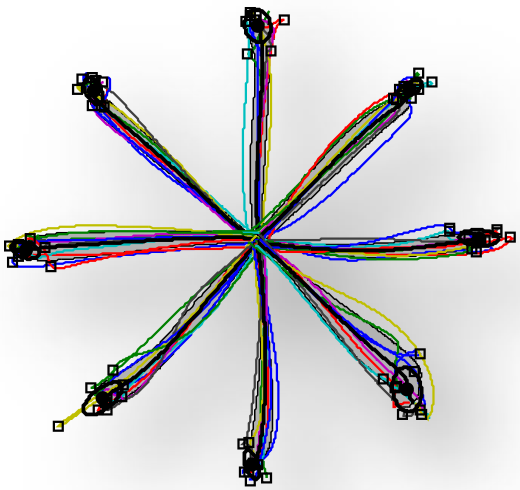
Experimental Procedures



Teleoperation

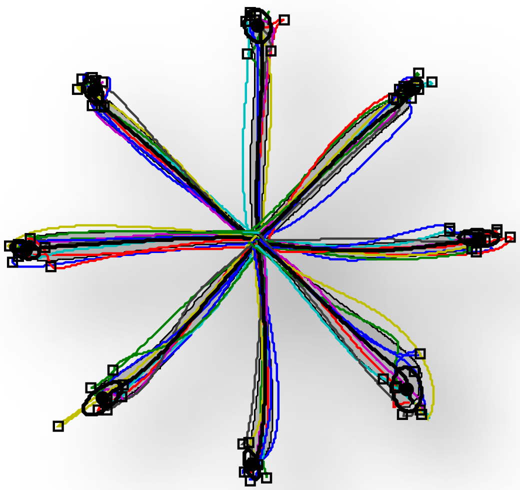
Freehand

Kinematics



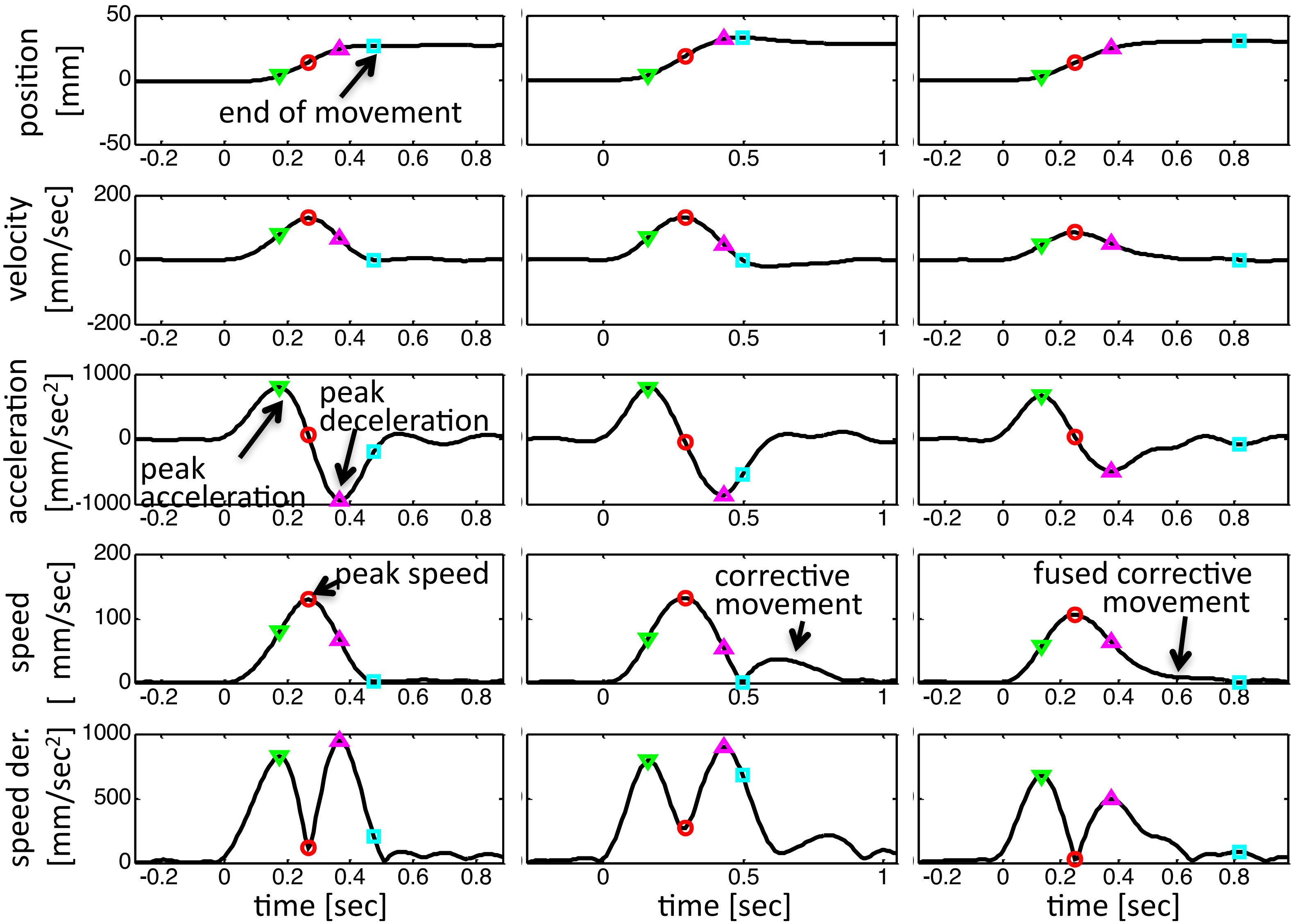
Variability

Kinematics



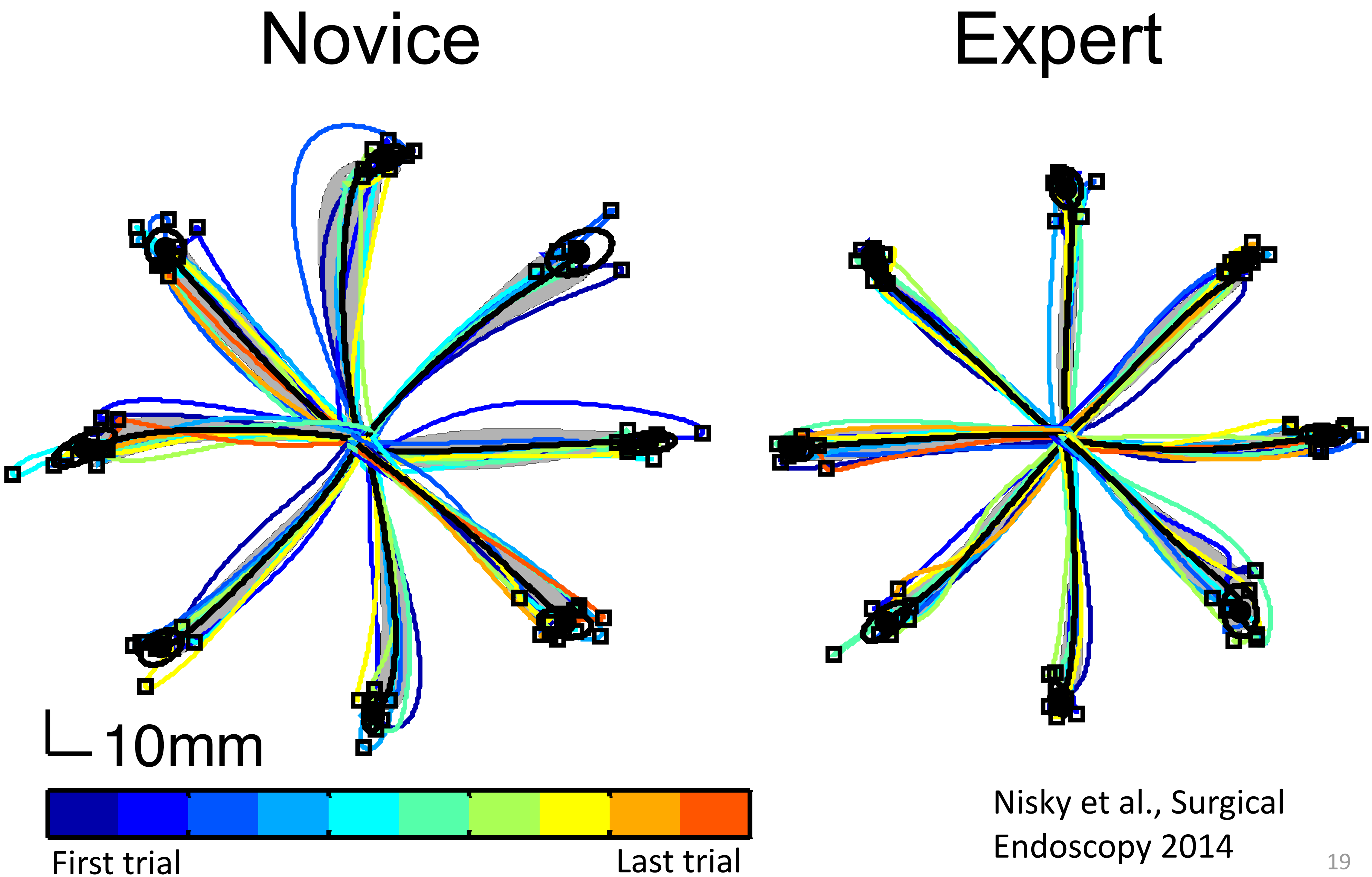
Variability

Data Analysis - Reach



Nisky et al., MMVR2013

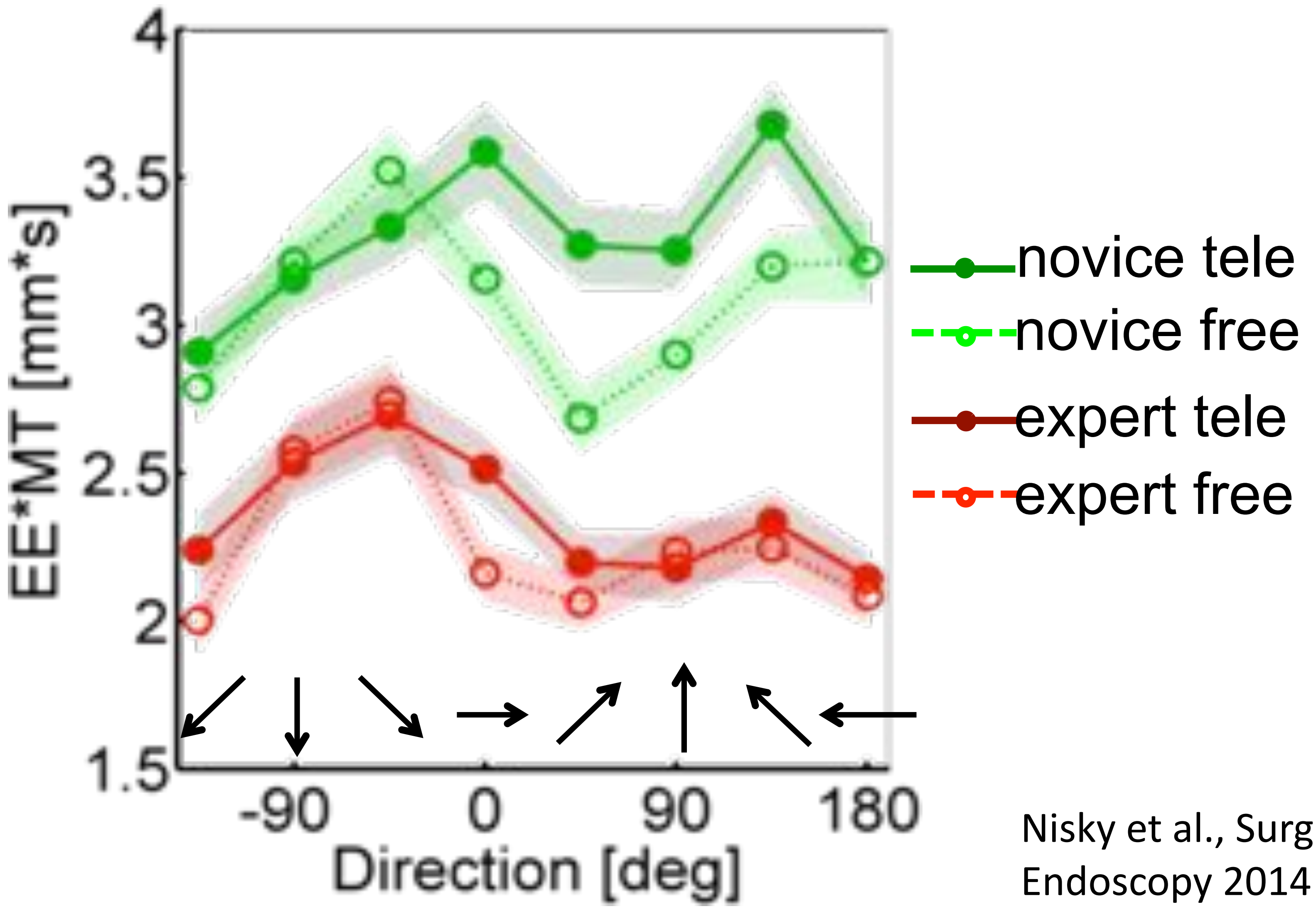
Deviation from Straight Line



Nisky et al., Surgical Endoscopy 2014

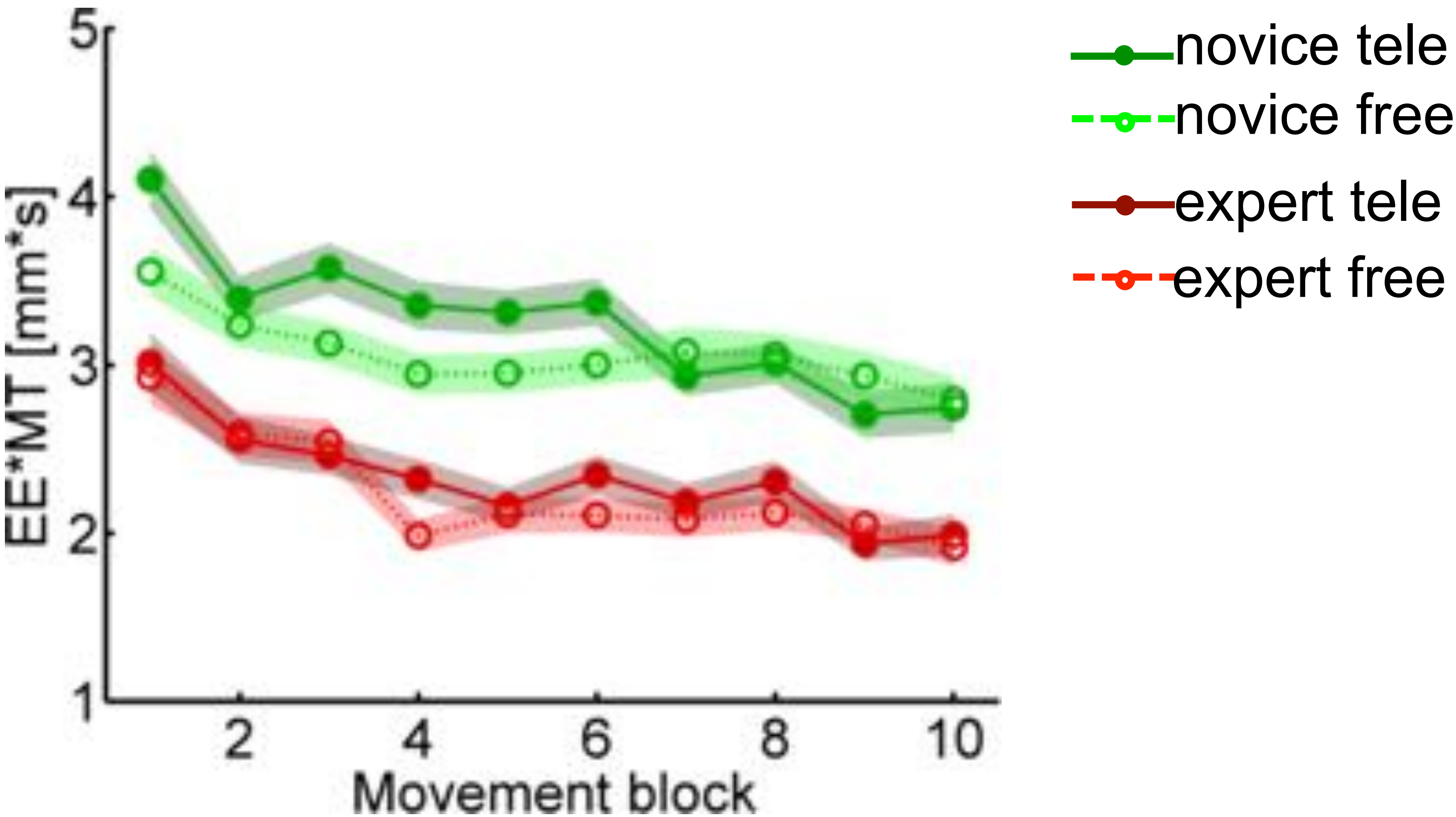
Performance

Endpoint Error * Movement Time



Nisky et al., Surgical Endoscopy 2014

Learning effects

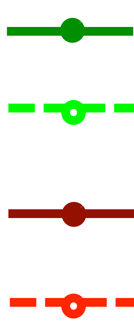


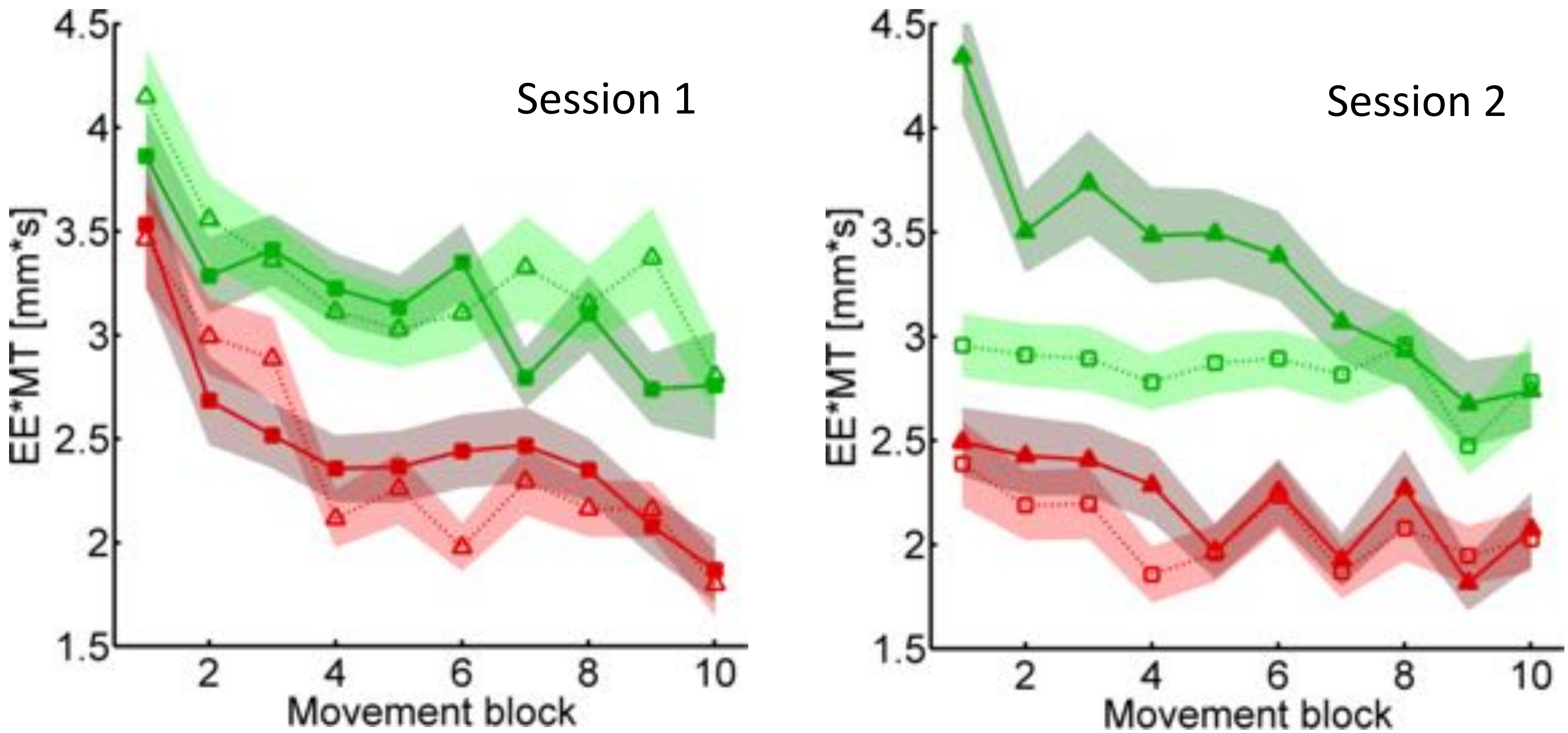
Nisky et al., 2014

Learning effects

All groups learn the task within 3-4 movement blocks in the first session

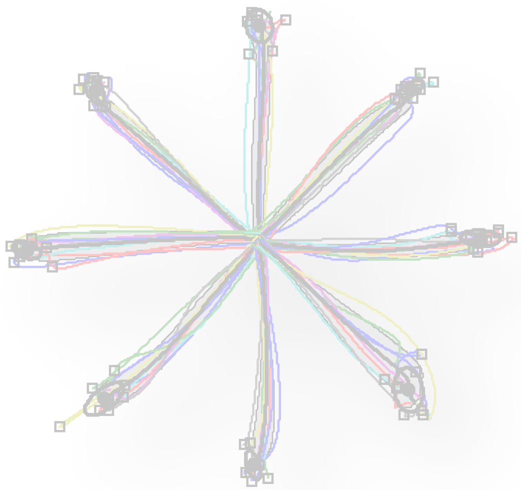
Teleoperating novices also learn system dynamics





Nisky et al., 2014

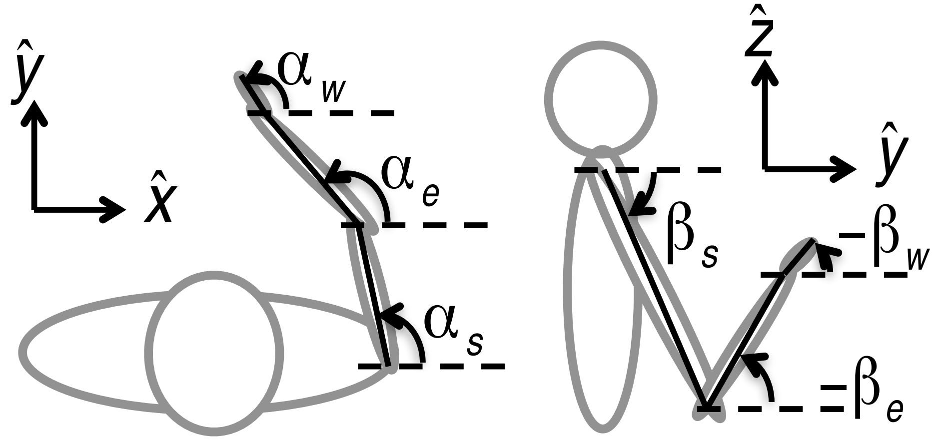
Kinematics



Variability

Redundancy and Variability

Human arm is a **redundant** manipulator

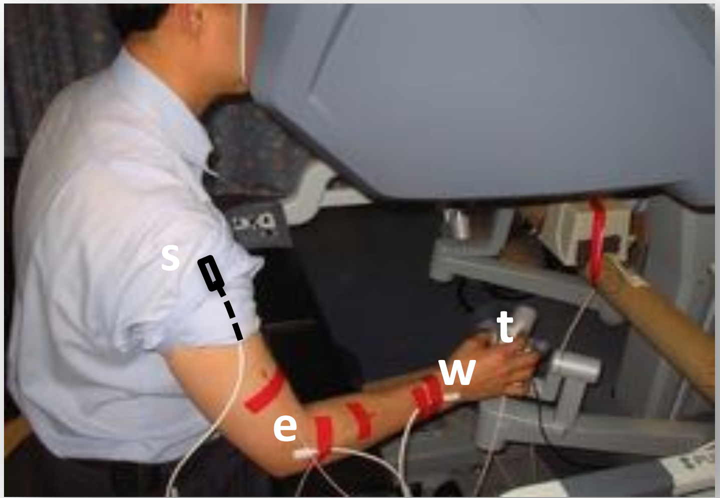


How is redundancy resolved?

- Bernstein, 1967

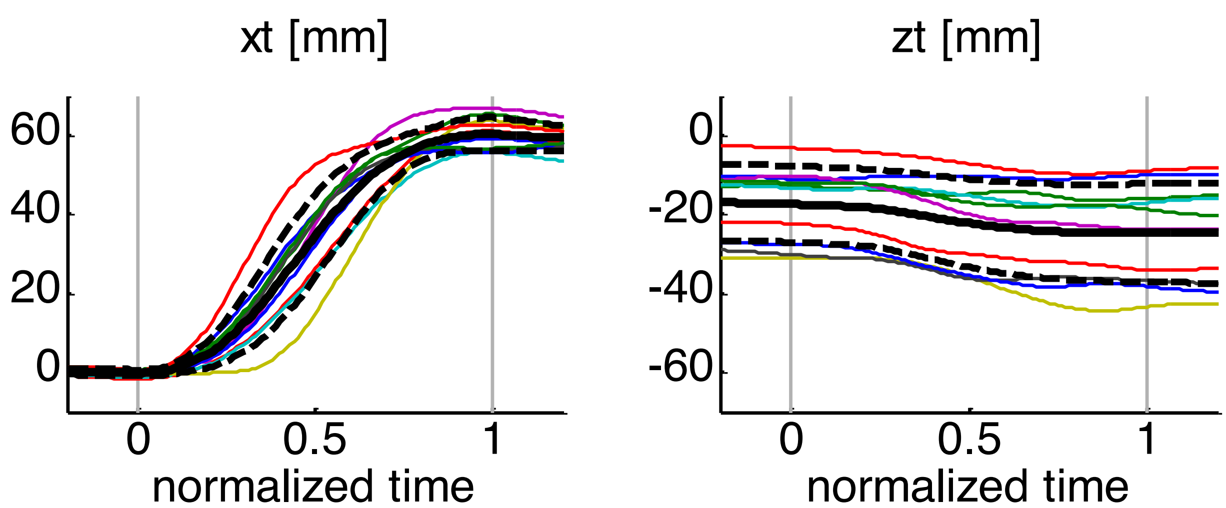
Motor system constrains only task relevant variability

- Uncontrolled Manifold Hypothesis
  Scholtz ans Schoner, 1999
- Minimum intervention principle
  Todorov 2002



Uncontrolled Manifold Hypothesis

Task space



Joint space

2 kinds of trial-to-trial variability in joint angles

- Changes task performance: V_{task}
- Doesn't change task performance: V_{other}

Variability coordination

$R_V = \log(V_{other}/V_{task})$

$R_V > 0$ stabilize

$R_V = 0$ independent

Nisky et al., ICRA 2013

Variability in Joint Space - Uncontrolled Manifold

Forward kinematics

$$\mathbf{x}[t] = F\left(\mathbf{q}[t]\right)$$

Linearize FWD kinematics

$$\mathbf{x}[t] - \overline{\mathbf{x}}[t] = \mathbf{J}(\overline{\mathbf{q}}[t])\left(\mathbf{q}[t] - \overline{\mathbf{q}}[t]\right)$$

Calculate null space

$$\mathbf{J}(\overline{\mathbf{q}}[t]) \cdot \mathbf{e} = 0$$

Project variance onto null and orthogonal spaces

$$\mathbf{q}_{\mathbf{UCM}}[t] = \mathbf{e}\mathbf{e}^{T}\left(\mathbf{q}[t] - \overline{\mathbf{q}}[t]\right)$$

$$\mathbf{q}_{\mathbf{ORT}}[t] = \left(\mathbf{q}[t] - \overline{\mathbf{q}}[t]\right) - \mathbf{q}_{\mathbf{UCM}}[t]$$

Calculate log of variance ratio

$$R_v[t] = \log\left(\frac{\sum_{i=1}^{N}\left(\mathbf{q}_{\mathbf{UCM}}[t]\right)^2 d_{ucm}^{-1} N^{-1}}{\sum_{i=1}^{N}\left(\mathbf{q}_{\mathbf{ORT}}[t]\right)^2 d_{task}^{-1} N^{-1}}\right)$$

Details in Nisky et al., ICRA 2013, Nisky et al., IEEE TBME 2014

Variability Predictions

XY movements are stabilized $R_V>0$

Z movements are not $R_V=0$

Larger R_V of experts

Skill increases R_V (Muller and Sternad, 2004)

Smaller R_V in teleoperation

Coordination of Arm Posture Variability

The task requires only accurate XY movements

XY movements $R_V>0$

Z movements $R_V=0$

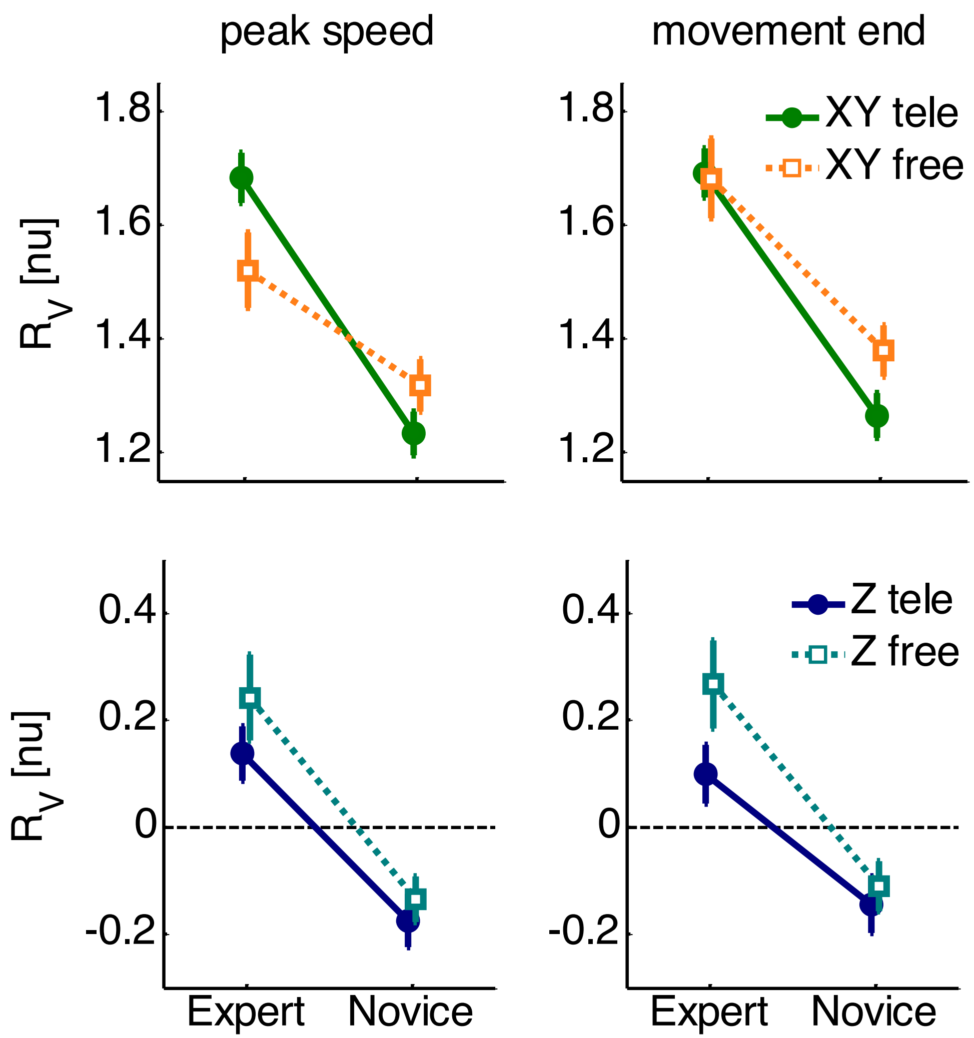
Experience

Larger R_V of experts

Teleoperation

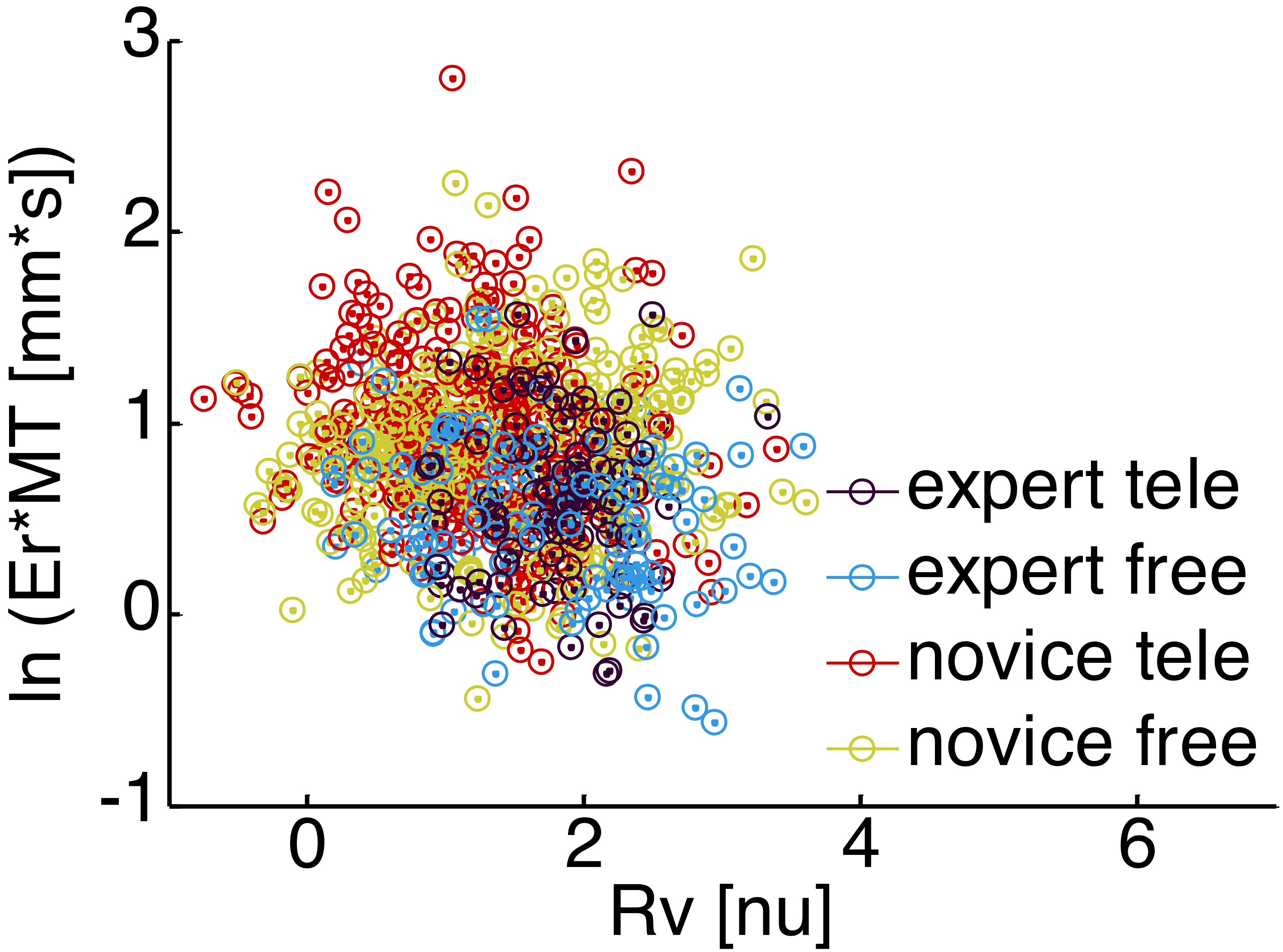
Experts R_V increase

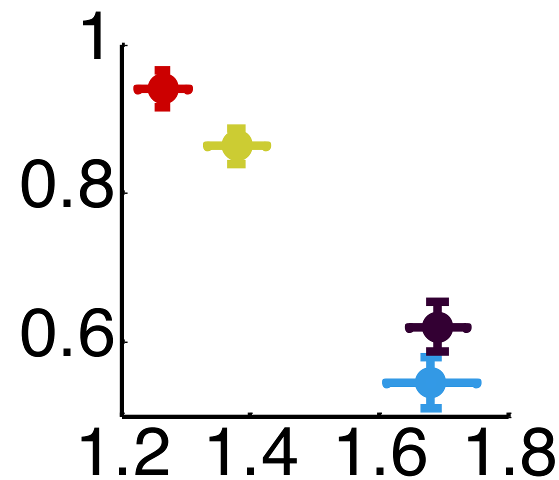
Novices R_V decrease



Nisky et al., IEEE TBME 2014

Rv and Performance





Nisky et al., IEEE TBME 2014

“Dexterous” Task: Needle driving

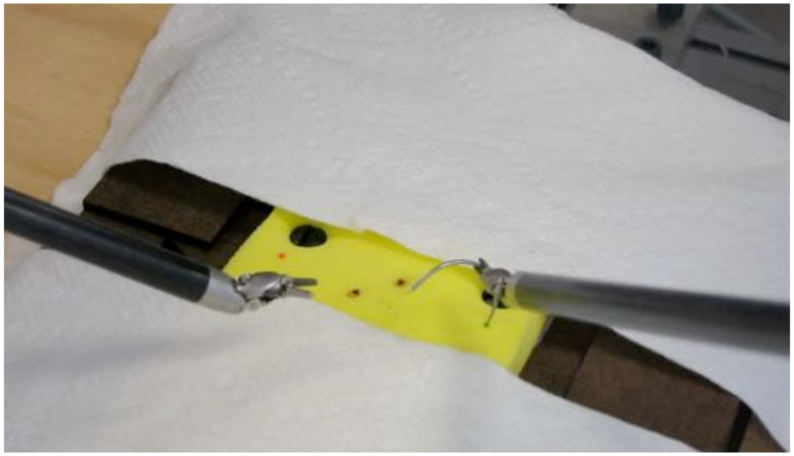
Clinically relevant movement

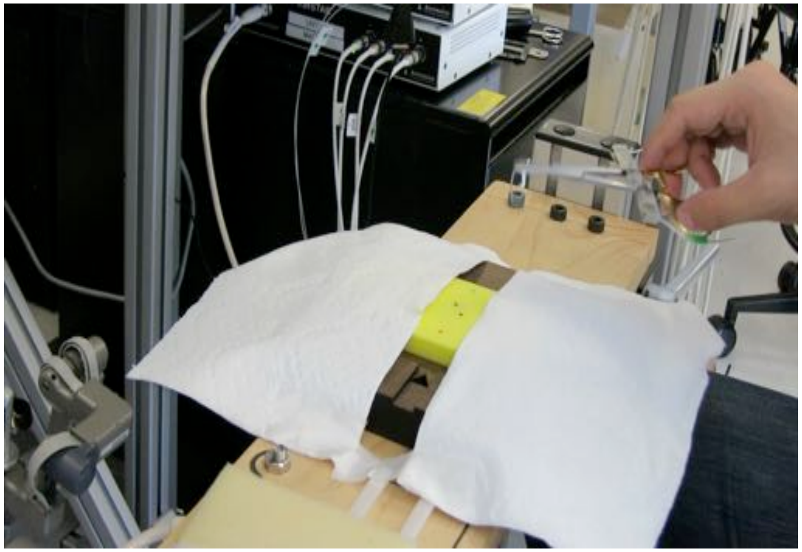
Complexity

- 3D movement
- Tissue interaction
- Orientation is critical

Conditions and participants

- Teleoperated v. open
- Experienced surgeons v. novices





Nisky et al., ICRA 2015

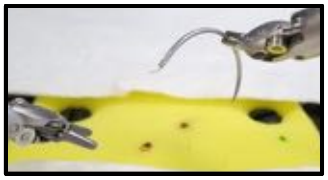
Experimental Setup

Teleoperated - dVRK

Open – magnetic tracking instrumented needle driver

Needle Driving Task

1


2


3

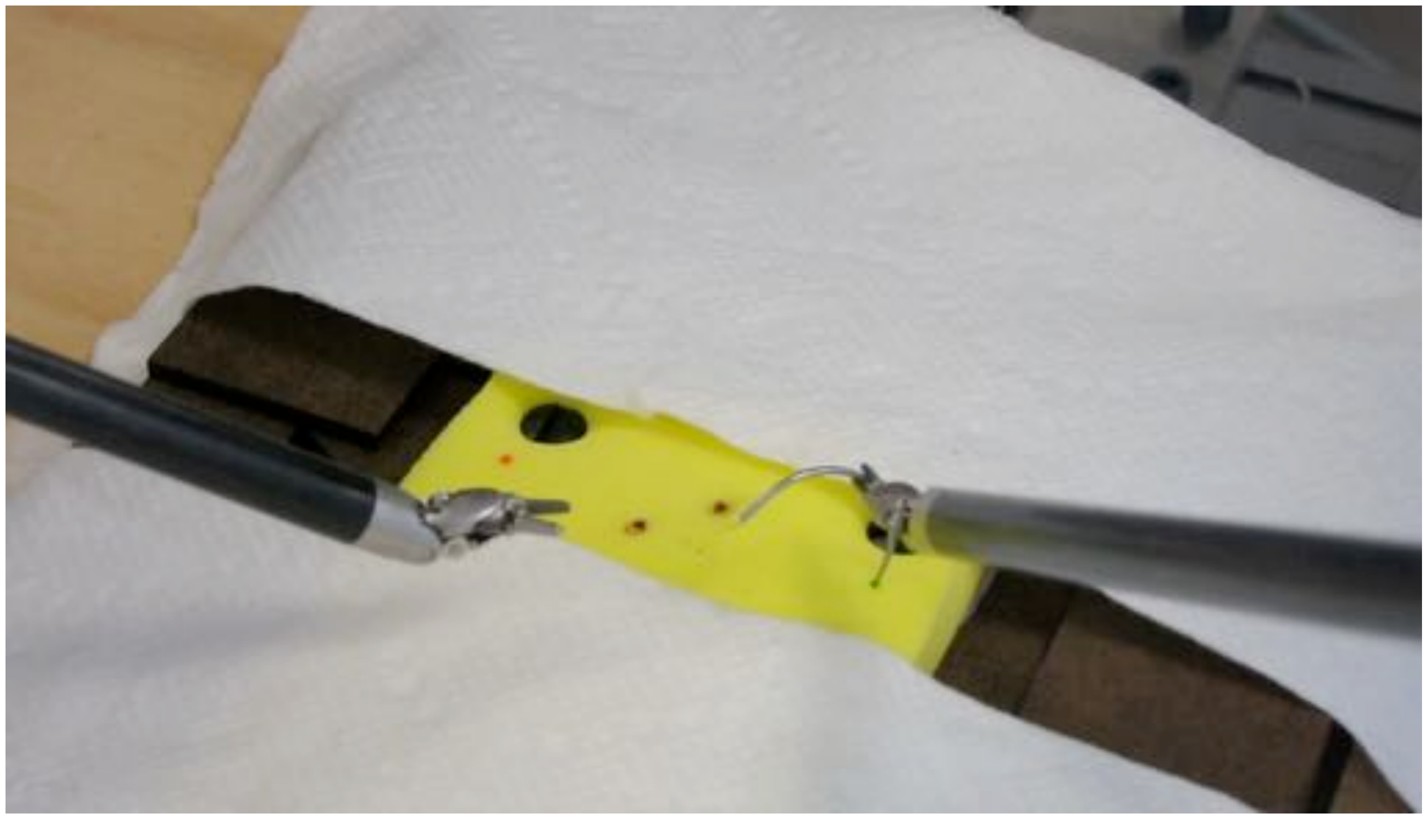

4


5

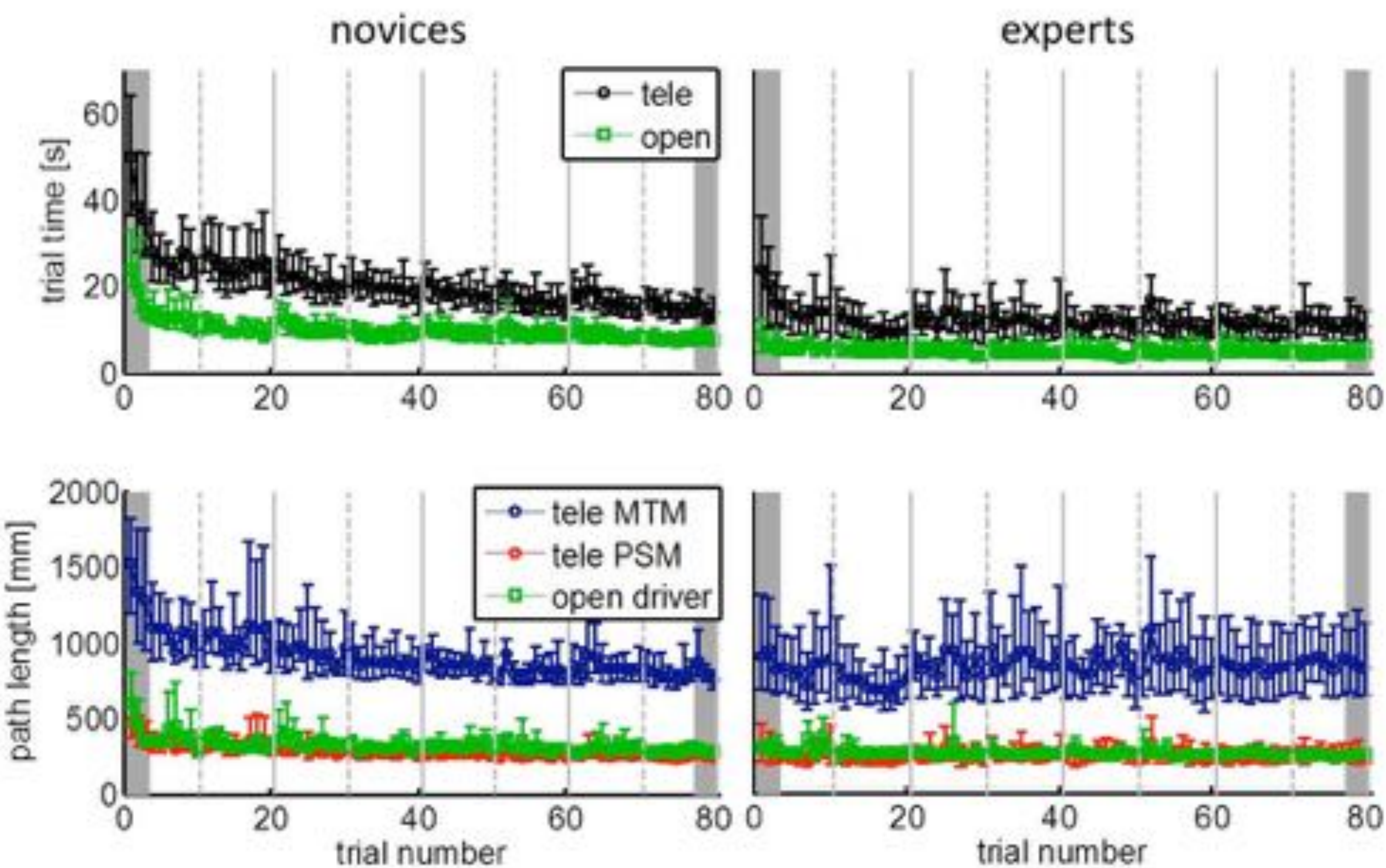

6


7


8

Learning Curves

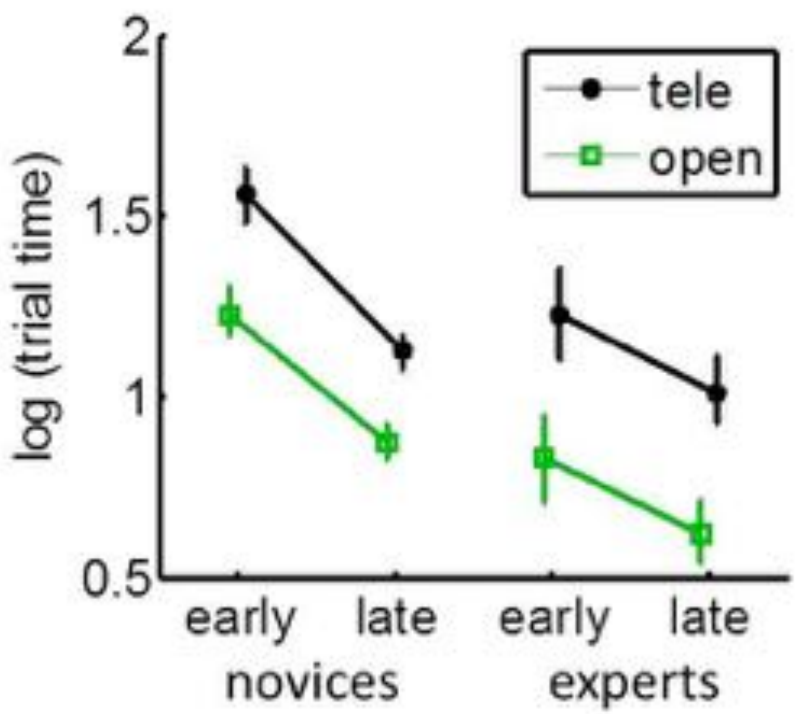


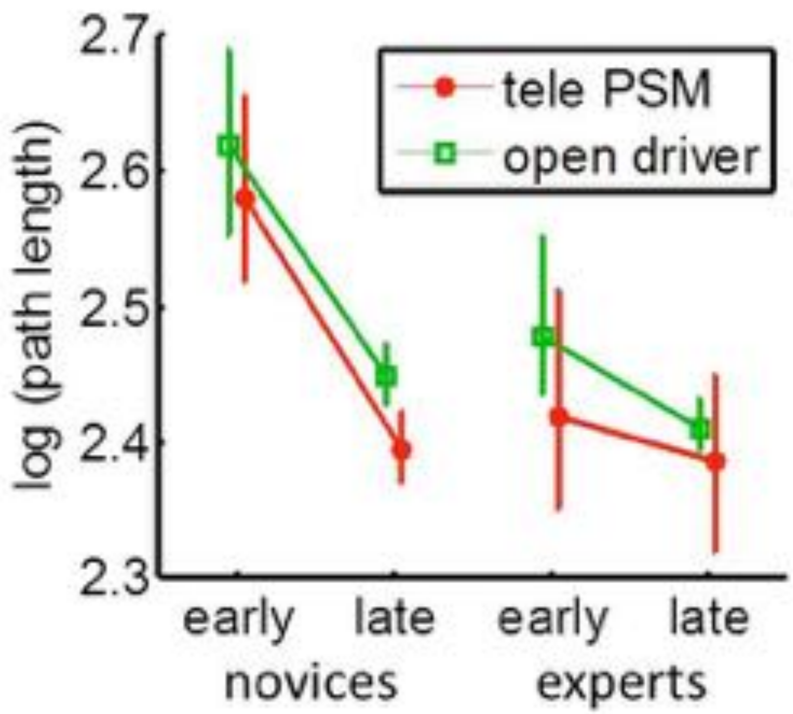
Learning Curves Summary

Open needle driving is faster, but with same needle path length

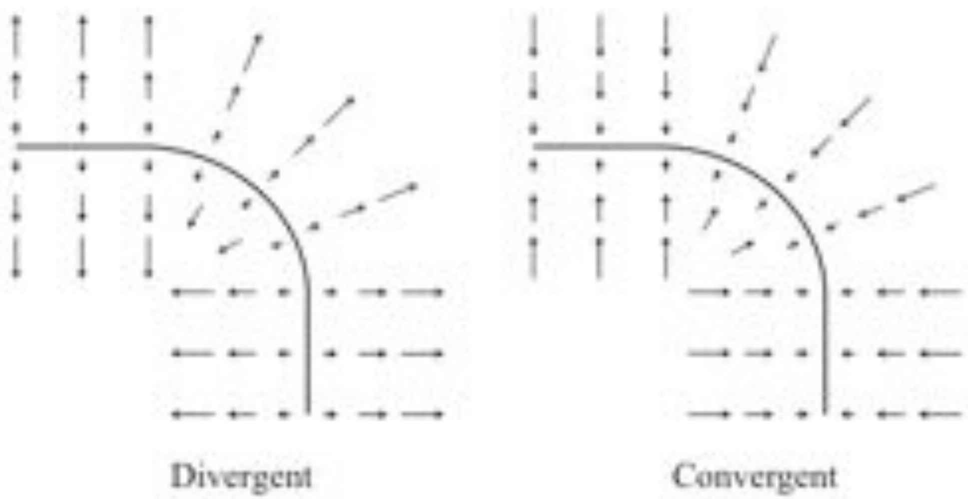
All participants improve movement time

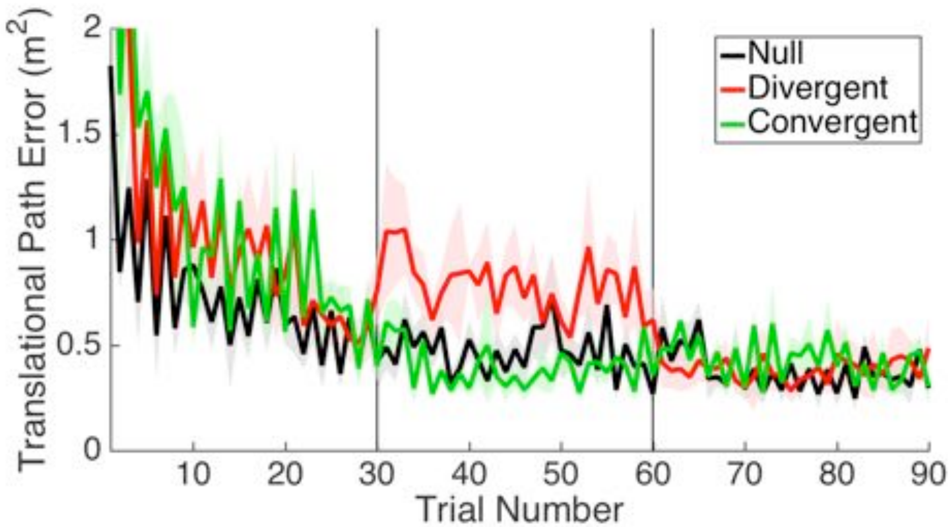
Only novices improve movement length





Training a manipulation task





Coad et al., submitted

Conclusions

The dynamics of the master manipulator matter

Experts have adapted and are better

Experts exploit the redundancy of their arm more than novices, especially in teleoperation

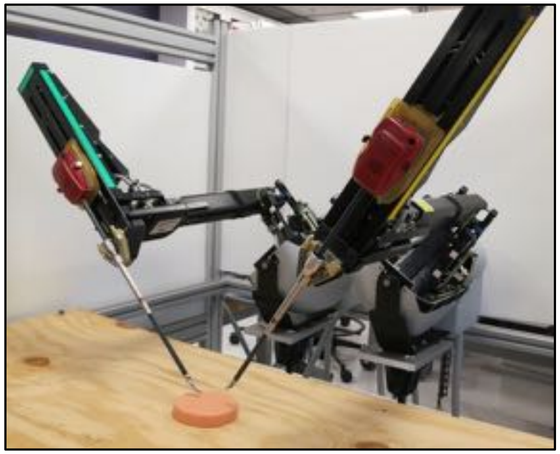
Learning trends also exist during manipulation

Resistive training may improve learning and performance

Future Work

Analysis of interaction forces and **dynamic modeling** of user in teleoperation and freehand

Analysis of redundancy exploitation in needle driving experiment



What is the role of haptic feedback?

Take Home

To build robotic systems that are operated by **humans**, we should:

- Study the **human operator**
- Apply findings to design, control, and training

Operators interact with robotic devices

- This allows us to study the **human operator** in unprecedented ways

Thank You

This work was supported by:

- Marie Curie International Outgoing Fellowship
- Weizmann Institute of Science National Postdoctoral Award for Advancing Women in Science
- Intuitive Surgical Technology Research Grant
- Stanford University