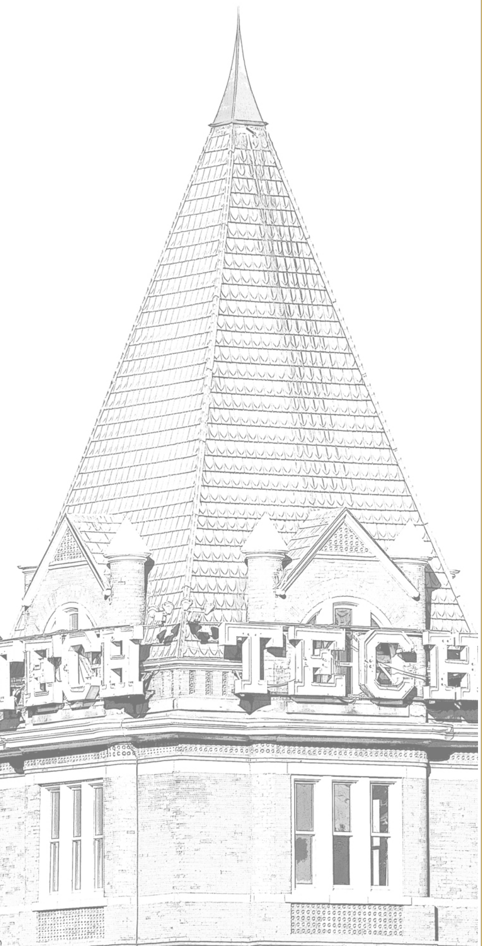

Human-Robot Physical Interaction for Neuromuscular Adaptive Robot Co-workers

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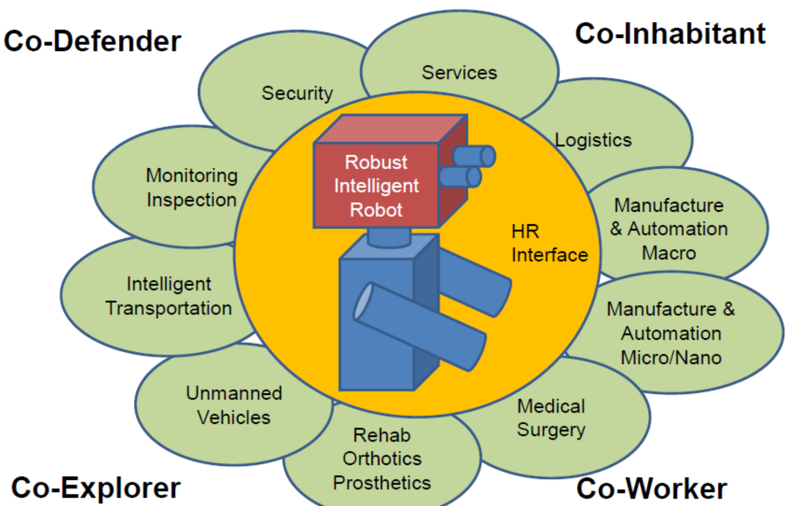
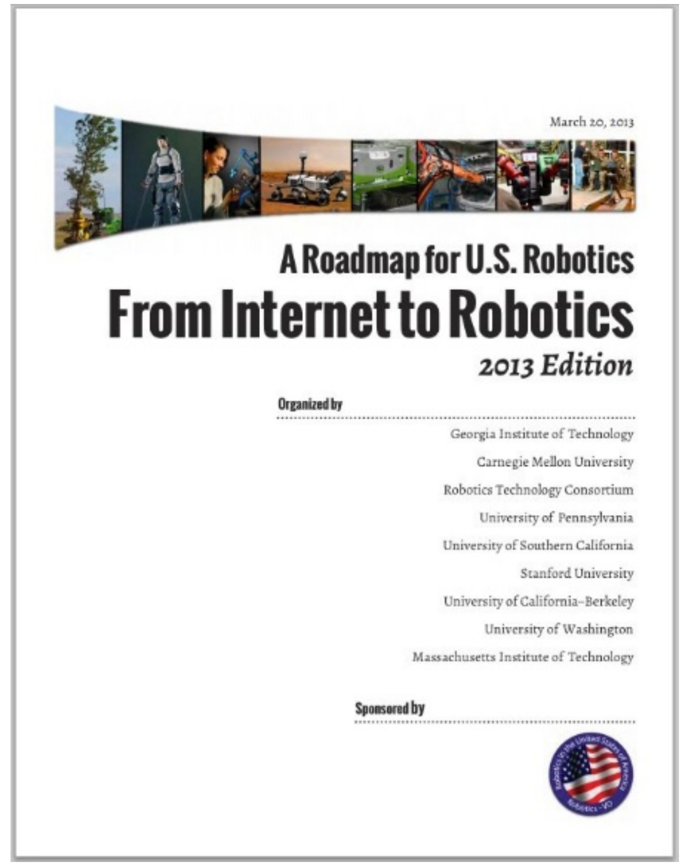
Georgia Institute of Technology

NATIONAL ROBOTICS INITIATIVE (NRI)

CMU, June 24th, 2011





March 20, 2013

A Roadmap for U.S. Robotics

From Internet to Robotics

2013 Edition

Organized by

Georgia Institute of Technology
Carnegie Mellon University
Robotics Technology Consortium
University of Pennsylvania
University of Southern California
Stanford University
University of California–Berkeley
University of Washington
Massachusetts Institute of Technology

Sponsored by

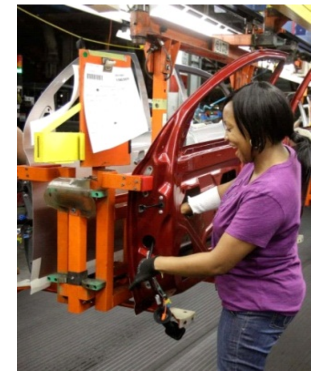
CLINICAL NEED: HEMIPARESIS

- A paralysis of one side of the body widely observed in stroke survivors
- 600,000 individuals suffer strokes each year in the U.S.
- Restricts activities of daily living (ADLs)

- Neural plasticity
- Physical therapy is an intensive process
- Unsatisfactory outcomes performed by unskilled therapists
- Scientific evaluation needed (e.g., fMRI)

INDUSTRIAL NEED: WORKER SAFETY

- Industry still largely relies on manual assembly by human workers (e.g., automobile, aerospace, construction…)

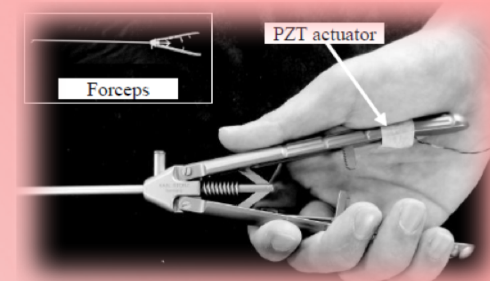


- Force assistance
- Work-related musculoskeletal disorders (WMSDs)
  e.g., Back injuries
- Situational awareness
- Skill training & assessment

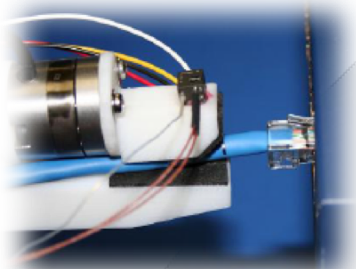
Motor control (Applied Physiology)

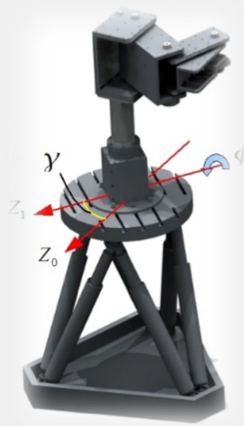

Wheelchair evaluation


Exoskeleton



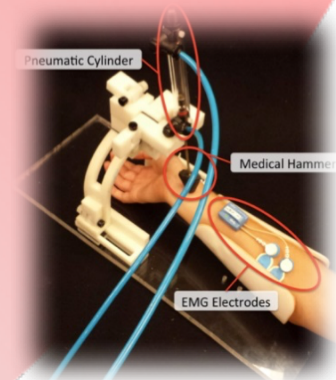
Sensorimotor function enhancement


Robotic assembly and error detection



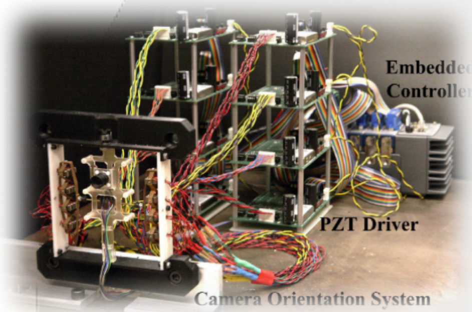
Deployable arm


Force-assisting system

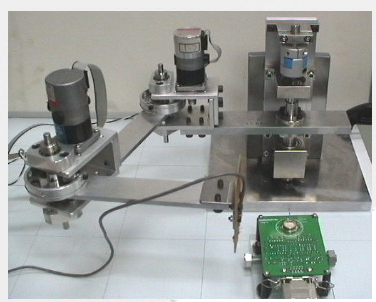


Paired associative stimulation for stroke rehabilitation


Teleoperation

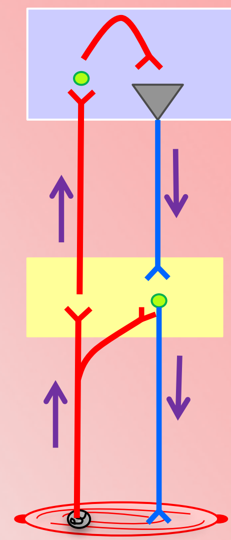


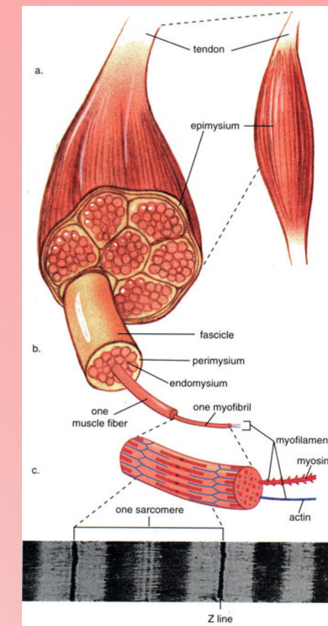
Robotic eye


High-speed servoing

Motion control

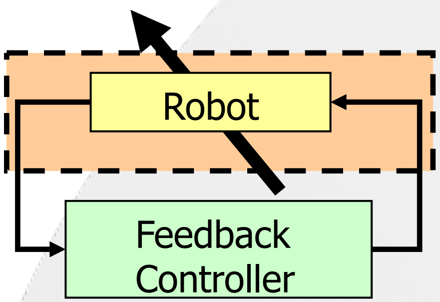
Motor control (Applied Physiology)

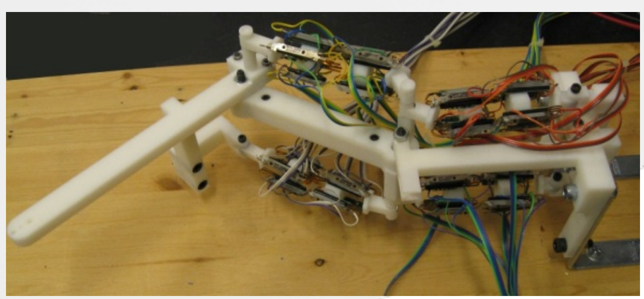




Biologically-inspired
Robotics

Rehabilitation Robotics
Assistive Robotics





Motion control

IS REHABILITATION ROBOTICS EFFECTIVE?

Georgia Tech

Conclusions. For subacute stroke participants with moderate to severe gait impairments, the diversity of **conventional gait training interventions appears to be more effective than robotic-assisted gait training** for facilitating returns in walking ability.

Neurorehabil Neural Repair January 2009 vol. 23 no. 1 5-13

Neurorehabilitation and Neural Repair
Volume 23 Number 1
January 2009 5-13

10.1177/1545968308326632
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Multicenter Randomized Clinical Trial Evaluating the Effectiveness of the Lokomat in Subacute Stroke

Joseph Hidler, PhD, Diane Nichols, PT, Marlena Pelliccio, PT, Kathy Brady, MSPT, Donielle D. Campbell, PT, Jennifer H. Kahn, PT, and T. George Hornby, PhD, PT

Objective. To compare the efficacy of robotic-assisted gait training with the Lokomat to conventional gait training in individuals with subacute stroke. *Methods.* A total of 63 participants <6 months poststroke with an initial walking speed between 0.1 to 0.6 m/s completed the multicenter, randomized clinical trial. All participants received twenty-four 1-hour sessions of either Lokomat or conventional gait training. Outcome measures were evaluated prior to training, after 12 and 24 sessions, and at a 3-month follow-up exam. Self-selected overground walking speed and distance walked in 6 minutes were the primary outcome measures, whereas secondary outcome measures included balance, mobility and function, cadence and symmetry, level of disability, and quality of life measures. *Results.* Participants who received conventional gait training experienced significantly greater gains in walking speed ($P = .002$) and distance ($P = .03$) than those trained on the Lokomat. These differences were maintained at the 3-month follow-up evaluation. Secondary measures were not different between the 2 groups, although a 2-fold greater improvement in cadence was observed in the conventional versus Lokomat group. *Conclusions.* For subacute stroke participants with moderate to severe gait impairments, the diversity of conventional gait training interventions appears to be more effective than robotic-assisted gait training for facilitating returns in walking ability.

Keywords: *Hemiplegia; Rehabilitation; Gait; Recovery of function; Robotics; Walking*

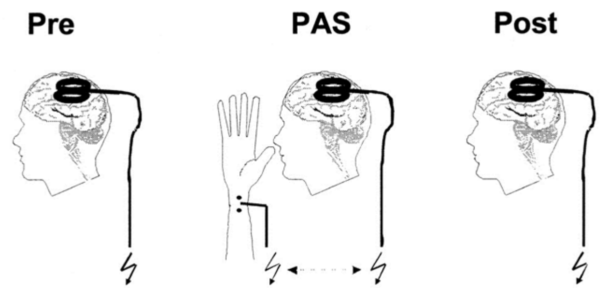
Body-weight supported locomotor training on a treadmill (BWSTT) has been the focus of intense investigations for nearly 20 years, beginning with the seminal work of Barbeau and colleagues.[1,2] Hesse et al[3] first evaluated this training modality in stroke populations, where it was demonstrated in a small group of subacute stroke participants that improvements in walking ability were greater following BWSTT than conventional physiotherapy. One uncertainty of this early work was whether the catalyst for improvements in walking ability resulted from the volume of steps practiced on the treadmill or the incorporation of body-weight support during training sessions. Visintin et al[4] investigated this by training 100 stroke participants on a treadmill, but only half received body-weight support. They found that the participants who received BWSTT demonstrated significantly greater gains in walking ability over those who received example, Sullivan et al[6] and Pohl et al[7] each evaluated the influence of training speeds on gait outcomes. Both of these studies found that participants trained at high speeds tend to show greater improvements in walking ability than those trained at slower rates. These and other studies using BWSTT in individuals poststroke demonstrate the effectiveness of the therapeutic paradigm, and have identified training factors that regulate intensity, which can directly impact the intervention outcomes.[8]

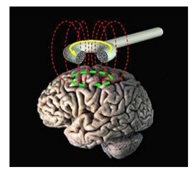
One of the recognized limitations with BWSTT is the significant demand it places on the therapists during training sessions. Specifically, manually assisting individuals with spastic hemiparesis at the impaired limb and/or trunk to facilitate continuous stepping may present significant physical challenges to skilled therapists. As a result, the consistency and duration of the training may be compromised. For

PAS: PAIRED ASSOCIATIVE STIMULATION

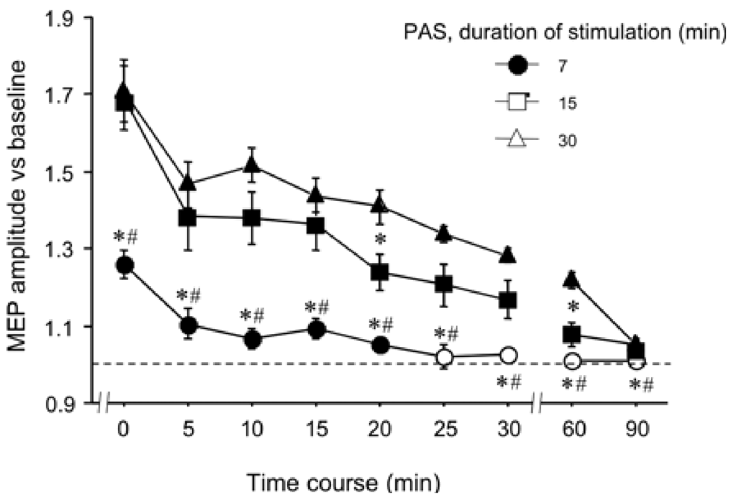
Transcranial magnetic stimulation (TMS)
&
Electrical peripheral stimulation

A





B



A: *Cartoons for explaining the experimental procedure.*
B: *Potentiated motor evoked potential (MEP) after PAS (Post) of different durations, compared with Pre*

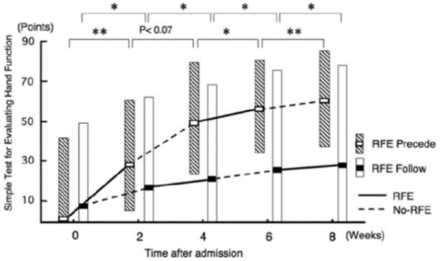
Nitsche MA, *et al*, Timing-dependent modulation of associative plasticity by general network excitability in the human motor cortex. *J Neurosci* 2007

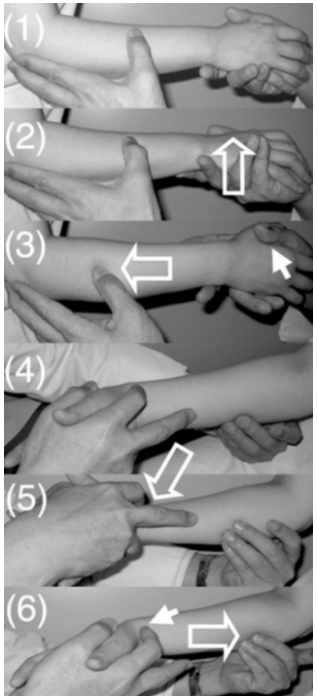
- Long-term potentiation (LTP) can be induced by PAS with electrical stimuli
- Observed increased motor excitability in the paretic lower limb of chronic stroke patients when walking*
- PAS may be used as an adjuvant therapy for stroke patients*

*Jayaram, G, *et al*. Contralesional paired associative stimulation increases paretic lower limb motor excitability post-stroke. *Experimental Brain Research,* 2008

- Induces stretch reflexes by tendon tapping
- Promising clinical results

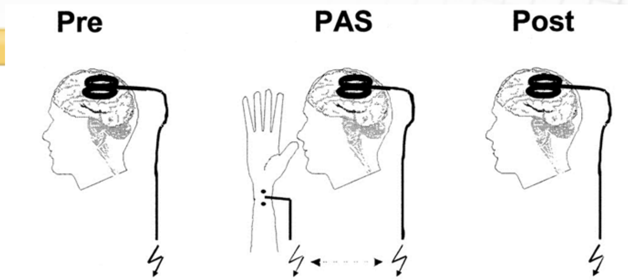
Dr. Kawahira, MD, Kagoshima University, Japan

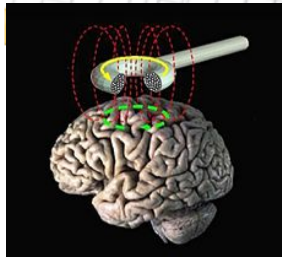




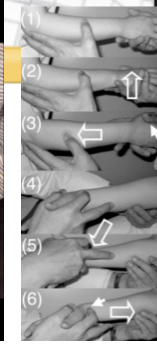
Kawahira K, *et al*. *Journal of Rehabilitation Medicine* 36: 159-64, 2004
Kawahira K, *et al*. *International Journal of Rehabilitation Research* , 2009
Kawahira K, *et al*. *Brain Injury* 24: 1202-13, 2010

NEUROMODULATION– PAS-INDUCED LTP

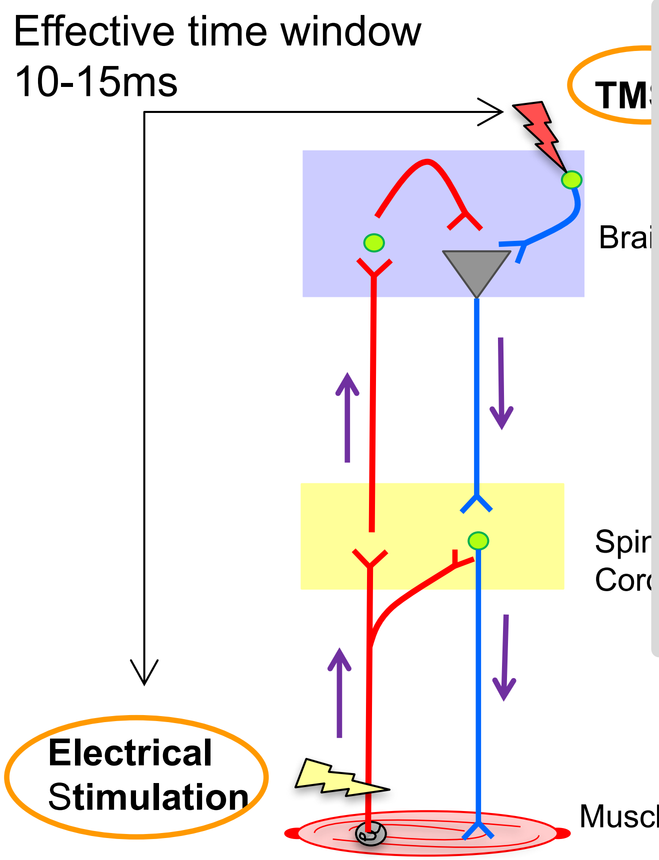


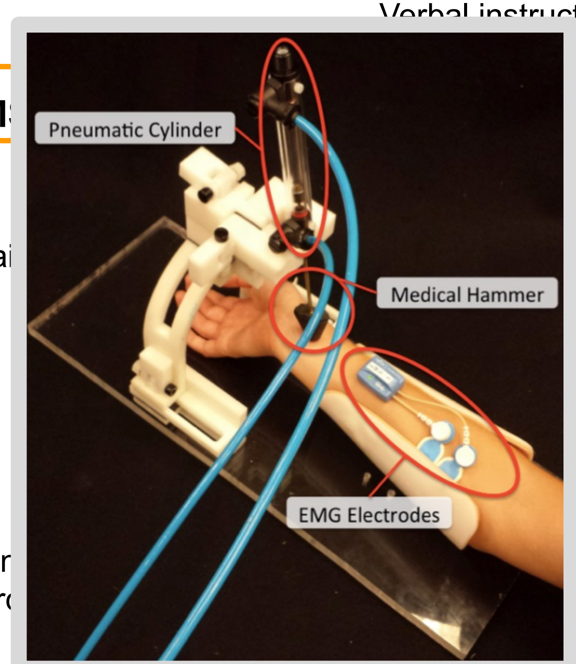


Physiology research

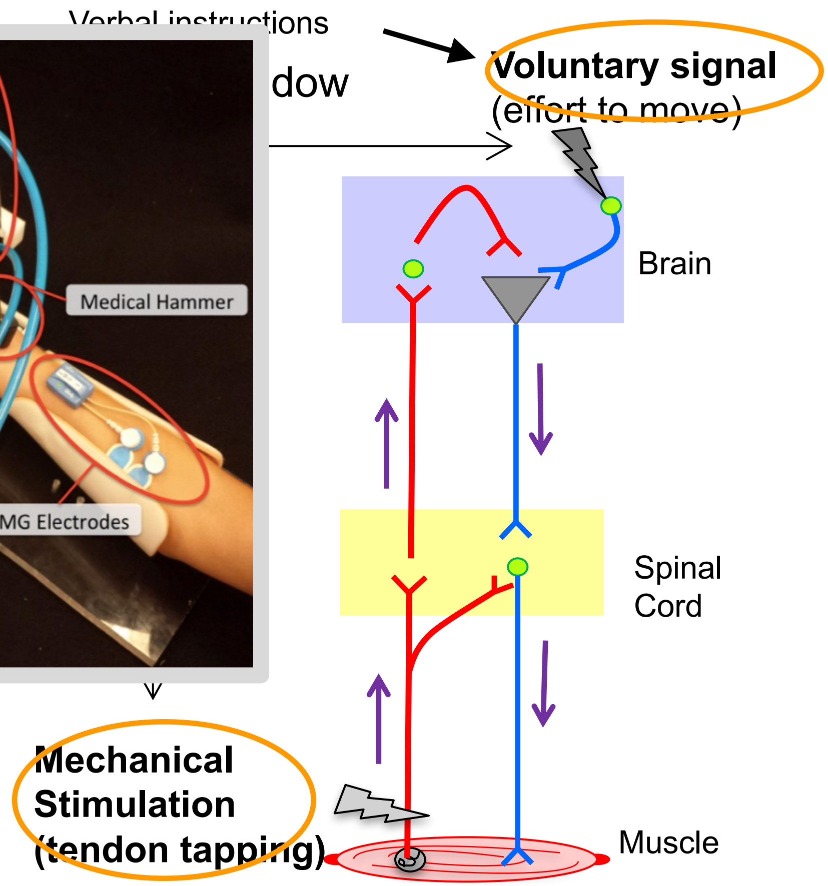


Clinical practice (Manual therapy)

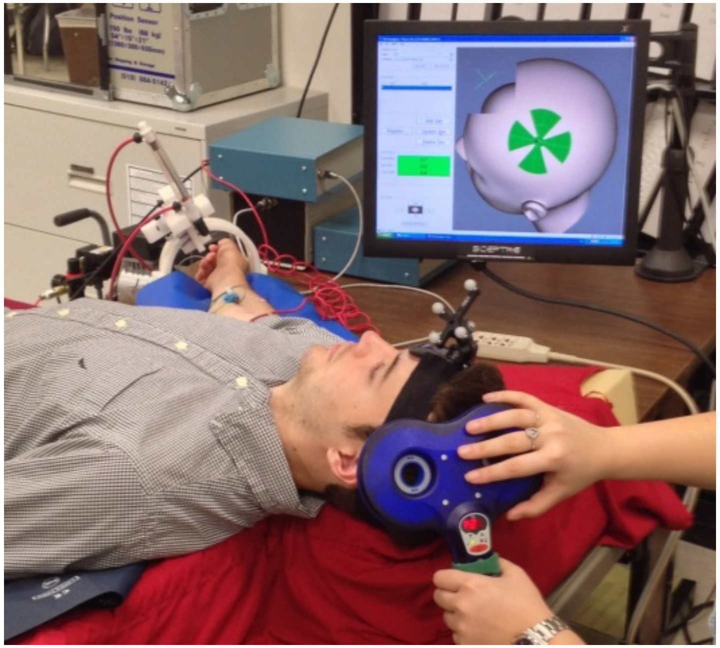


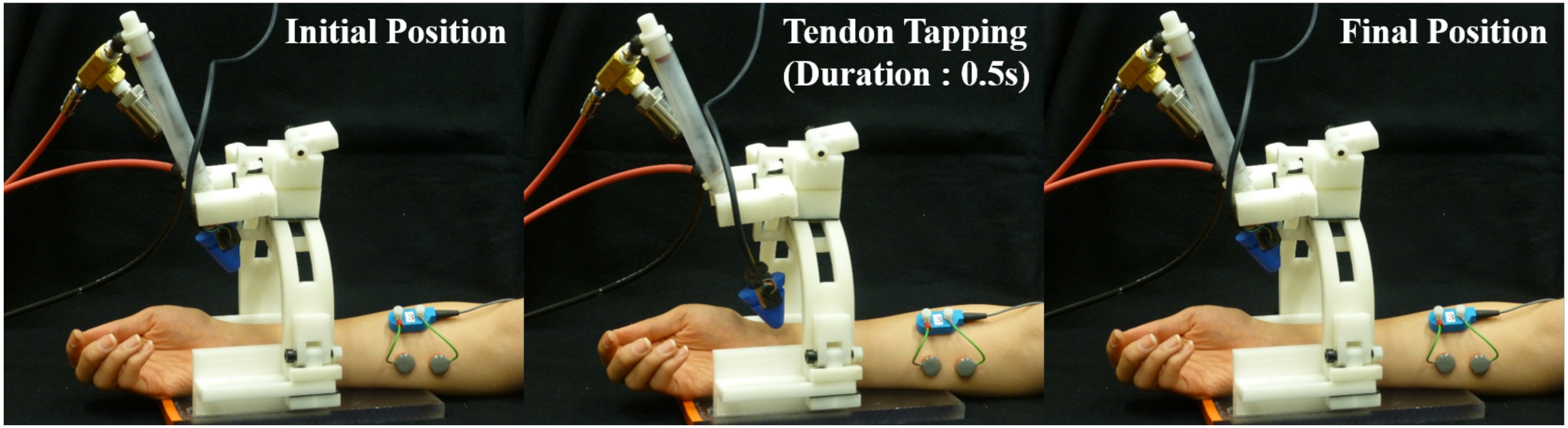


Peripheral
Nervous
System



ROBOTIC PAS FOR CORTICAL FACILITATION WITH AFFERENT STIMULATION

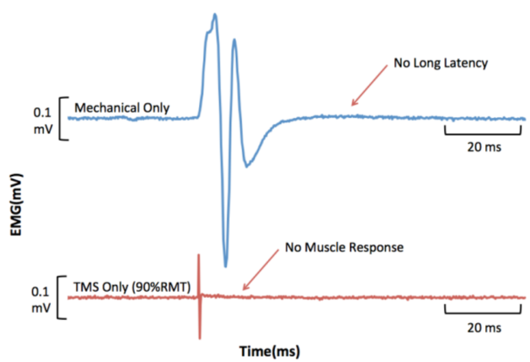




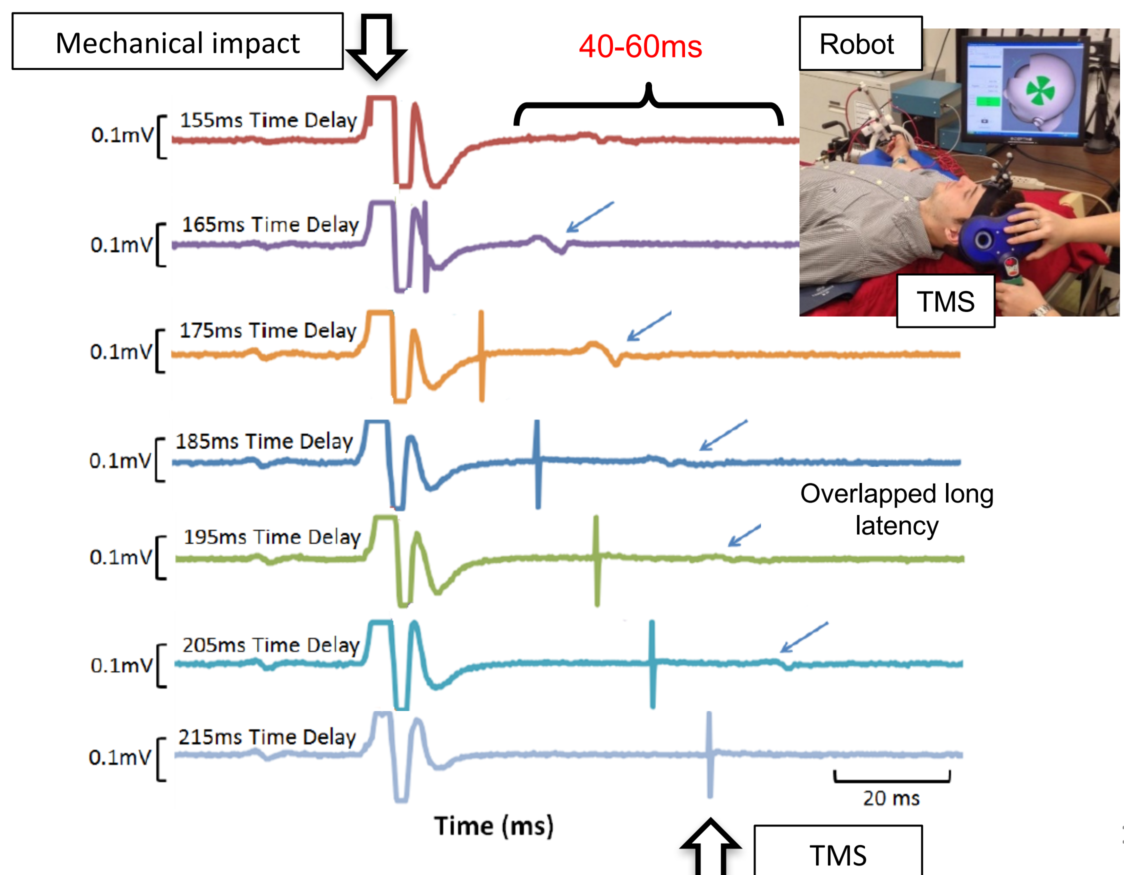
ROBOTICALLY PERFORMED PAS

- Successful synchronization between TMS and hammer hit across 40-60ms time frame
- Response more *dispersed* in time due to the desynchronized activation of muscle spindles

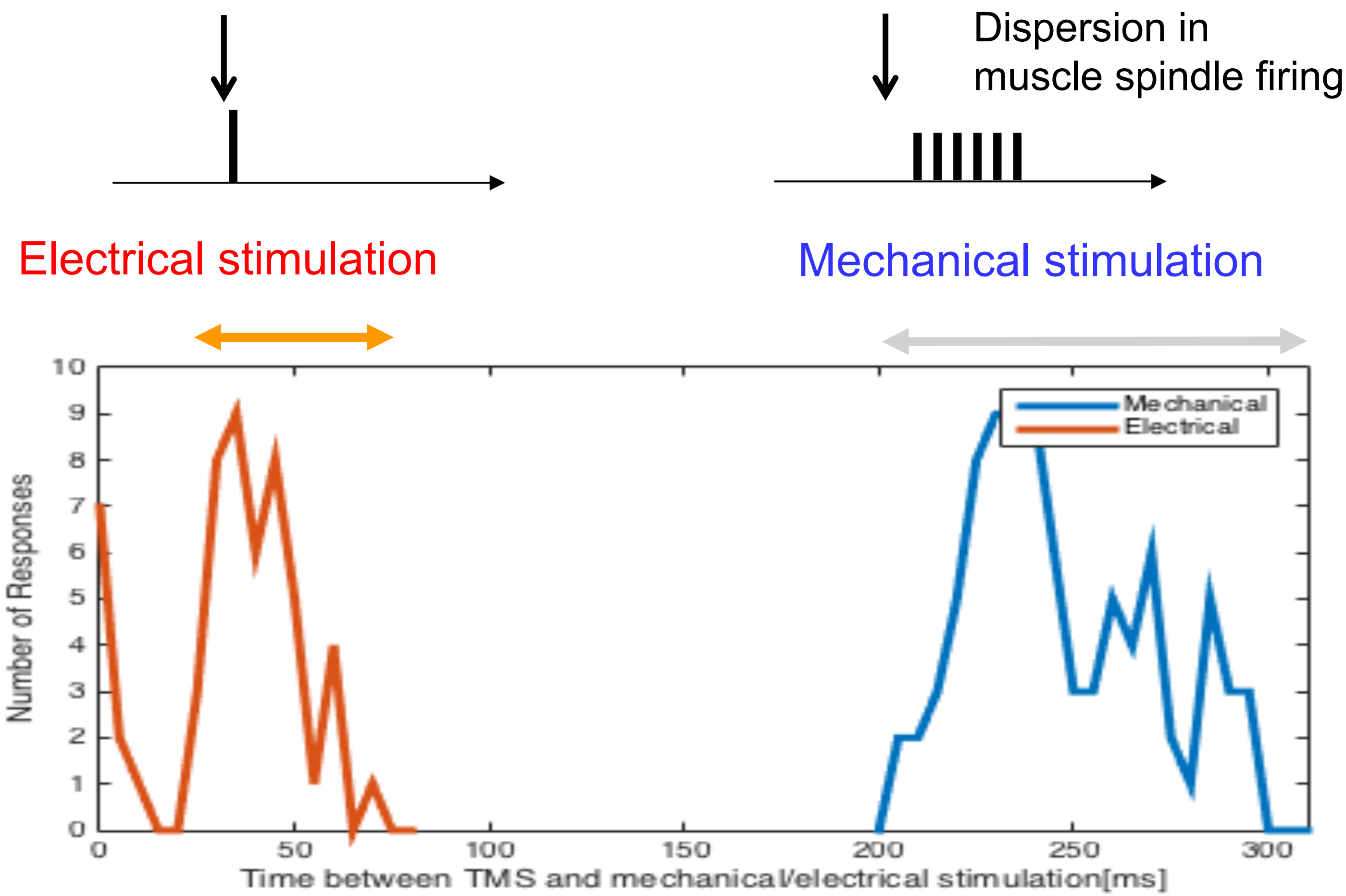
Mechanical Only



90% RMT TMS Only



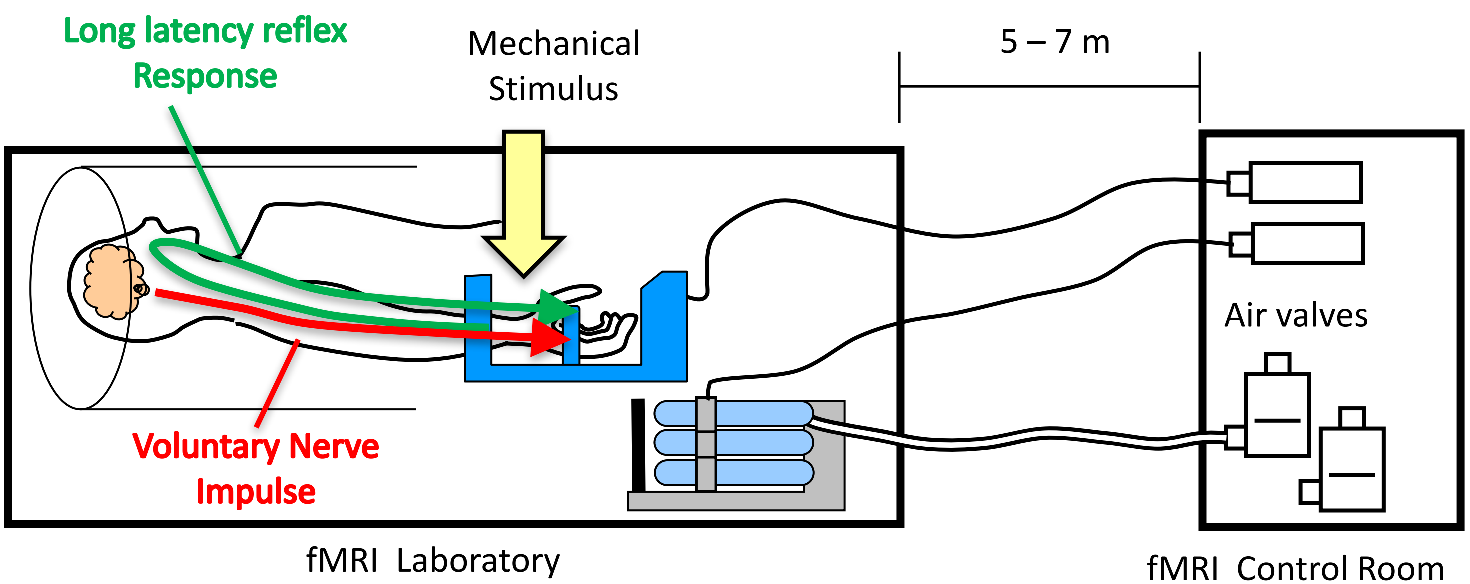
MECHANICAL VS ELECTRICAL STIMULATION



Euisun Kim, Ilya Kovalenko, Minoru Shinohara and Jun Ueda, Optimal Inter-stimulus Interval for Paired Associative Stimulation with Mechanical Stimulation, *Neural Plasticity*, under review.

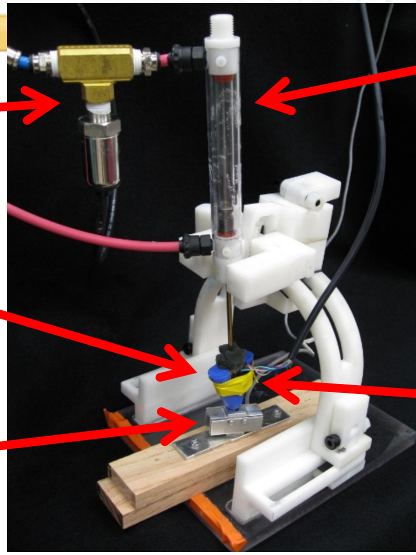
IS PNEUMATIC ACTUATION INACCURATE?

Required performance characteristics is NOT fast speed of response, BUT small variability in impact application

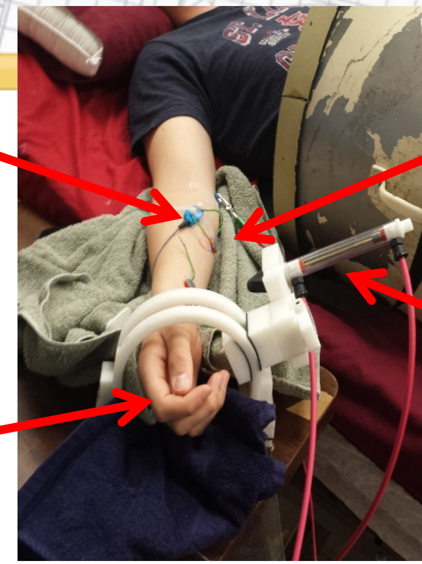


Observations:
Pure time delay is not significant (even for a 7.5m line)
Pressure attenuation is significant, but predictable
Hammer motion is highly repeatable (SD < 5ms)

TIMING ANALYSIS



Device only

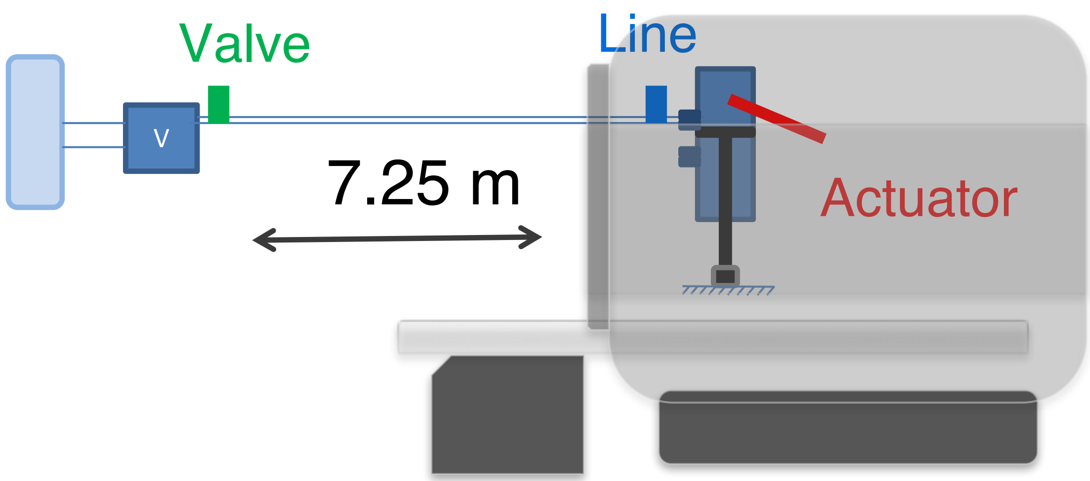


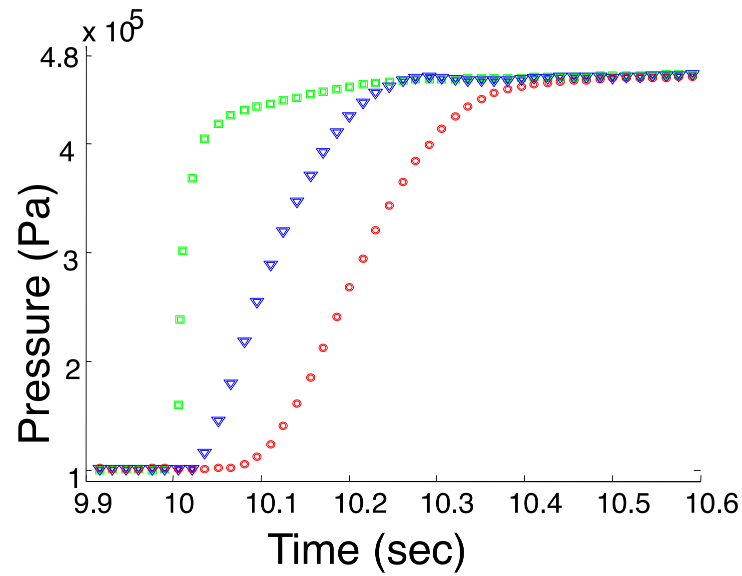
With subject

unit: ms		Top Chamber Fills Up	Hammer Starts to Extend	Hammer Hits Hand	Hammer Bounces Back to Hand	EMG Picks Up Mech. Stimulus
Force Sensor (50 Observations)	Average	523	621	688	690	N/A
	Standard Dev	**0**	**2**	**1**	**1**	N/A
	Range	[523, 523]	[617, 626]	[686, 690]	[689, 692]	N/A
Subject 1 (538 Observations)	Average	523	631	683	698	701
	Standard Dev	**0**	**5**	**4**	**4**	**4**
	Range	[523, 523]	[613, 640]	[669, 688]	[688, 704]	[689, 712]
Subject 2 (324 Observations)	Average	523	626	672	681	695
	Standard Dev	**0**	**4**	**2**	**2**	**2**
	Range	[523, 523]	[614, 650]	[666, 678]	[673, 688]	[689, 703]
Subject 3 (252 Observations)	Average	523	615	676	693	695
	Standard Dev	**0**	**2**	**1**	**1**	**1**
	Range	[523, 523]	[609, 625]	[674, 679]	[691, 696]	[692, 699]

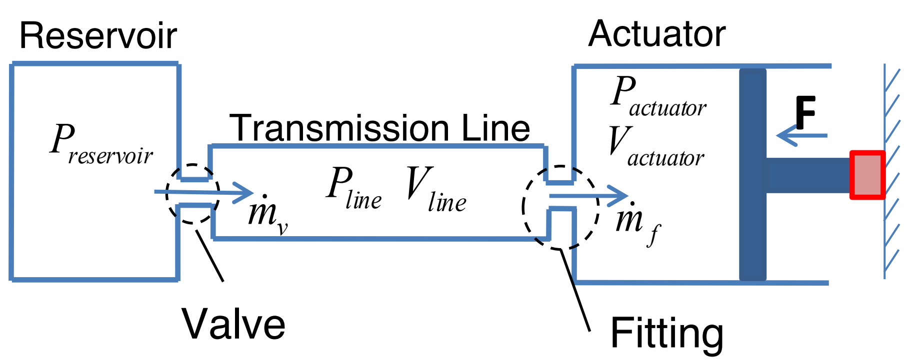
Euisun Kim, Ilya Kovalenko, Lauren Lacey, Minoru Shinohara, Jun Ueda, "Timing Analysis of Robotic Neuromodulatory Rehabilitation System for Paired Associative Stimulation", *IEEE Robotics and Automation Letters* (RA-L), Vol 1, Issue 2, pp: 1028–1035, February, 2016

PRESSURE CONTROL CHALLENGES



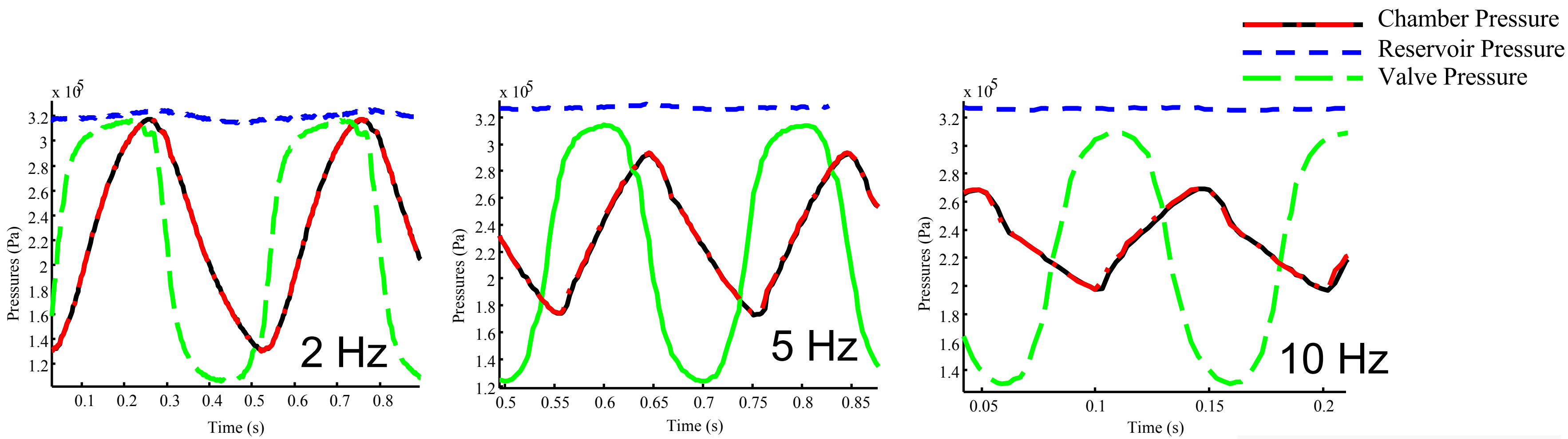


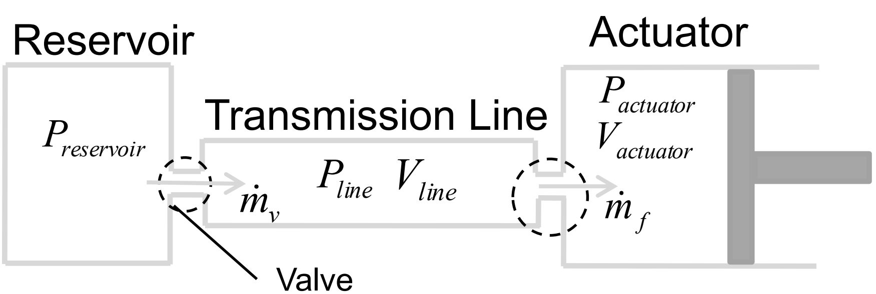
Solution: Closed-form 3-champer model and back-stepping control



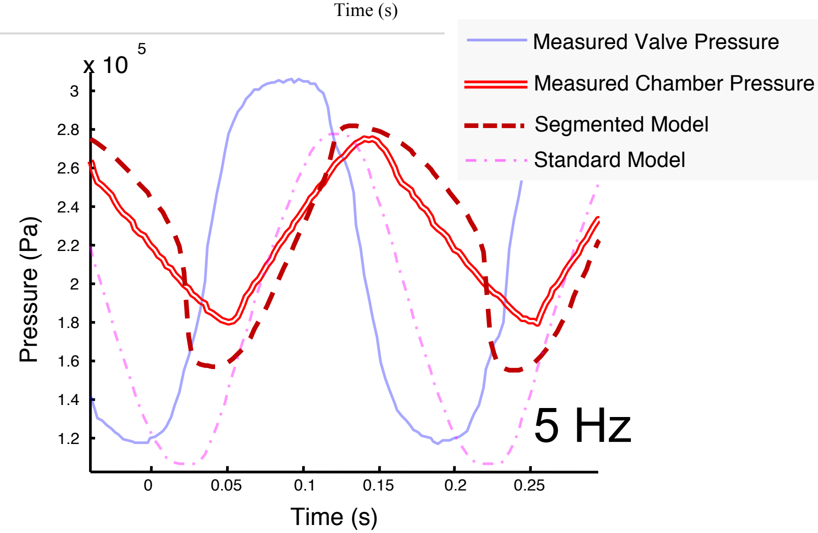
Melih Turkseven and Jun Ueda, An Asymptotically Stable Pressure Observer Based on Load and Displacement Sensing for Pneumatic Actuators with Long Transmission Lines, *IEEE /ASME Transactions on Mechatronics, 2017*

LINE DYNAMICS

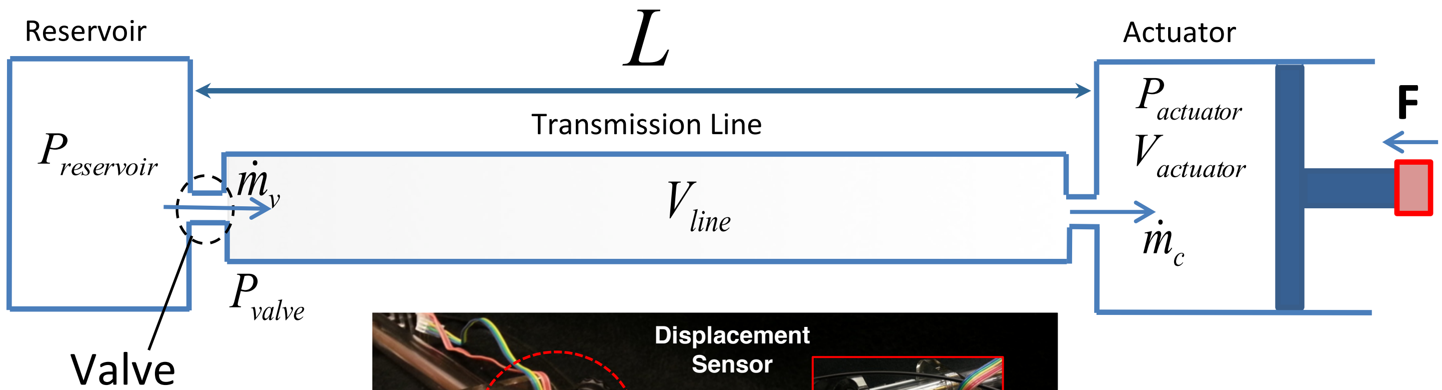


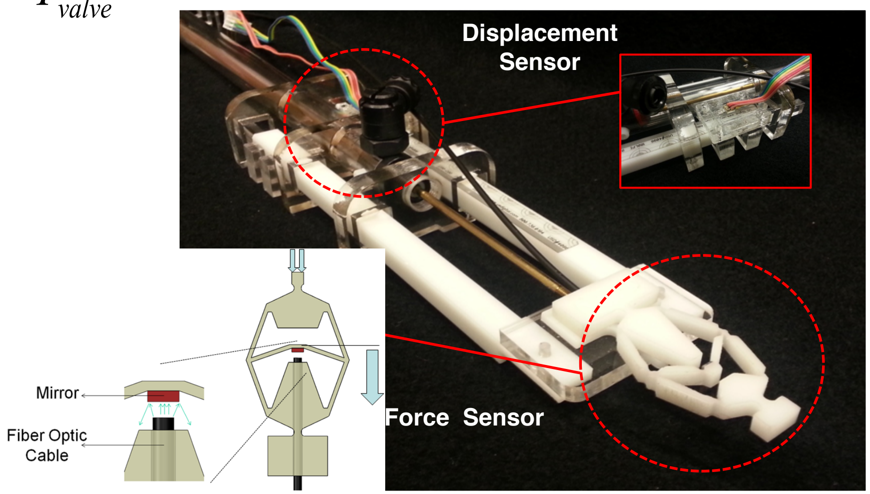


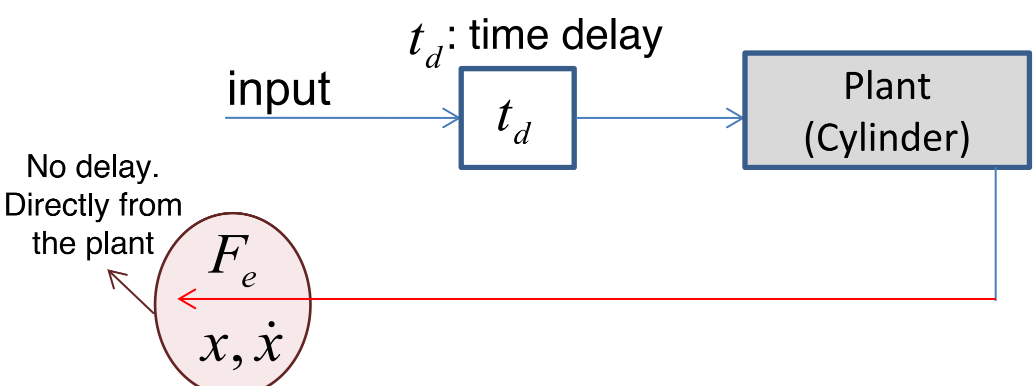
$$\frac{dP_{line}}{dt} = \frac{(\dot{m}_v - \dot{m}_f)RT}{V_{line}} \qquad \frac{d\dot{m}_f}{dt} = (\Delta P)A - f(\dot{m}_i, P_i)$$

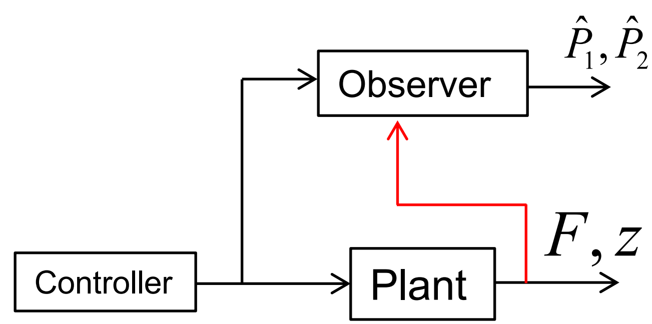


PRESSURE ESTIMATION(CONCEPT)









OBSERVER DYNAMICS

- Developed observer minimizes the error in the estimated actuator force
- Both force and displacement measurements are utilized

Isothermal chamber model, has been shown to be stable with regard to pressure estimation errors*:

$$\dot{\tilde{m}}_i(\tilde{P}_i) < 0 \quad \text{if} \quad A_{v_i} < 0 \quad \text{(de-pressurization)}$$

$$\dot{\tilde{m}}_i(\tilde{P}_i) \leq 0 \quad \text{if} \quad A_{v_i} > 0 \quad \text{(pressurization)}$$

*Gulati and Barth "*A Globally Stable, Nonlinear Pressure Observer for Pneumatic Actuators with Servo Valves*", ,2009

$$\dot{m}_i RT = P_i \dot{V}_i + \dot{P}_i V_i$$

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} P_1 V_1 \\ P_2 V_2 \end{pmatrix}$$

$$\begin{pmatrix} \dot{\hat{x}}_1 \\ \dot{\hat{x}}_2 \end{pmatrix} = \boxed{\begin{pmatrix} \dot{\hat{m}}_1 RT \\ \dot{\hat{m}}_2 RT \end{pmatrix}} + \boxed{k \begin{pmatrix} f_1 \\ f_2 \end{pmatrix}}$$

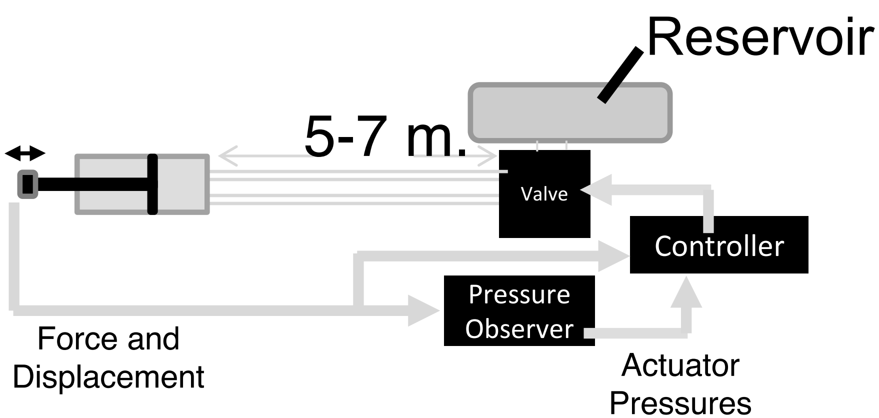
$$F_p = F_e + M\ddot{x} + B\dot{x}$$

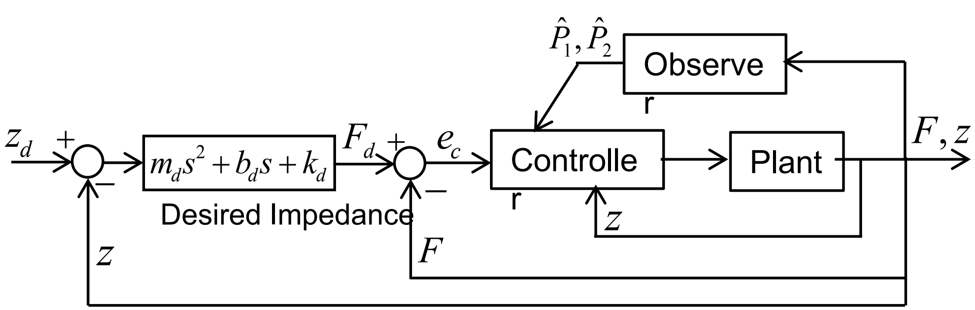
$$f_1 = -\frac{1}{V_1 A_2}(\hat{P}_1 A_1 - \hat{P}_2 A_2 - F_p)$$

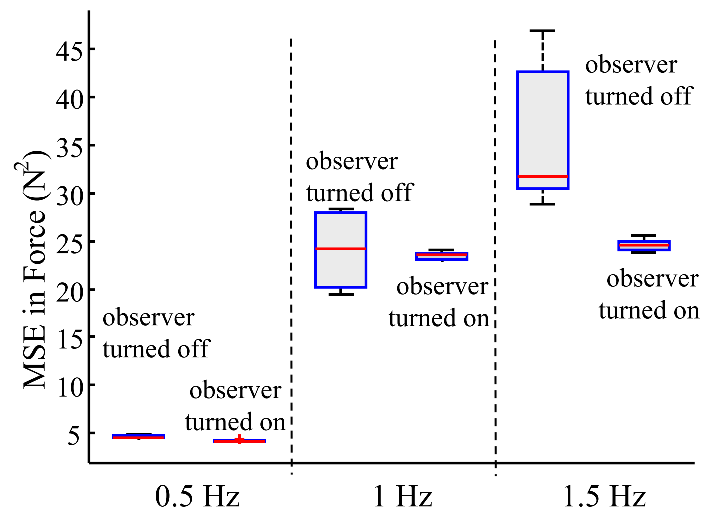
$$f_2 = \frac{1}{V_2 A_1}(\hat{P}_1 A_1 - \hat{P}_2 A_2 - F_p)$$

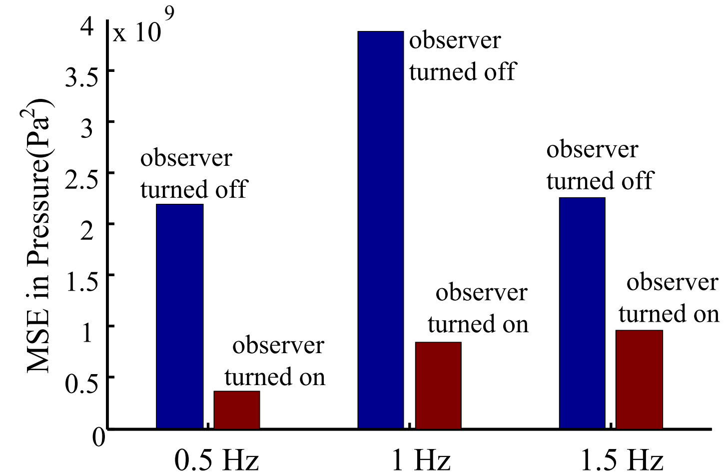
OBSERVER BASED (SIMPLE FEEDBACK) CONTROL

Compensates for the perturbations related to unmodeled dynamics



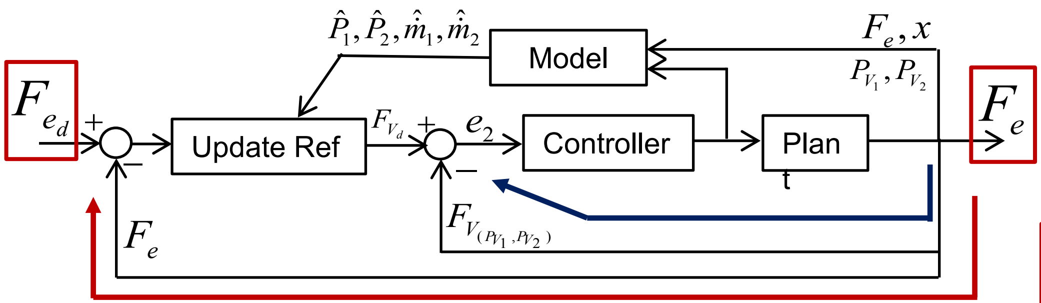






"BACK-STEPPING" CONTROL STRUCTURE

Georgia Tech



$$\dot{F}_e = F_V \bar{h} - F_P \bar{h} - G_1 + \delta_1(x)$$

$$\dot{F}_V = \frac{(\psi_1 + \psi_2)u - (\dot{m}_{C_1} A_1 + \dot{m}_{C_2} A_2)}{V_L/2} + \delta_2(x)$$

$$e_1 = F_{e_d} - F_e$$

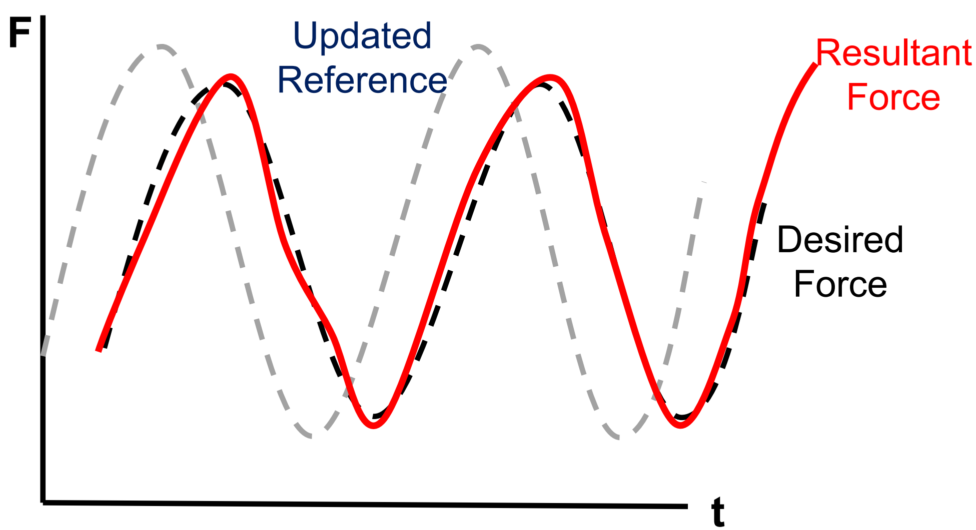
$$s_1 = e_1 + \lambda_1 \int e_1 dt$$

$$F_{V_d} = F_P + \frac{\lambda_1 e_1 + \dot{F}_{e_d} + G_1}{\bar{h}} + k_1 s_1$$

$$e_2 = F_{V_d} - F_V$$

$$s_2 = e_2 + \lambda_2 \int e_2 dt$$

$$u = \frac{(\dot{F}_{V_d} + k_2 s_2) V_L/2 + (\dot{m}_{C_1} A_1 + \dot{m}_{C_2} A_2)}{(\psi_1 + \psi_2)}$$



$$L = \frac{1}{2}(s_1^2 + e_2^2 + (\lambda_2 k_2 w_2)^2)$$

$$\dot{L} = -\bar{h} k_1 s_1^2 + \bar{h} e_2 s_1 + \delta_1 s_1 - k_2 e_2^2 + \delta_2 e_2$$

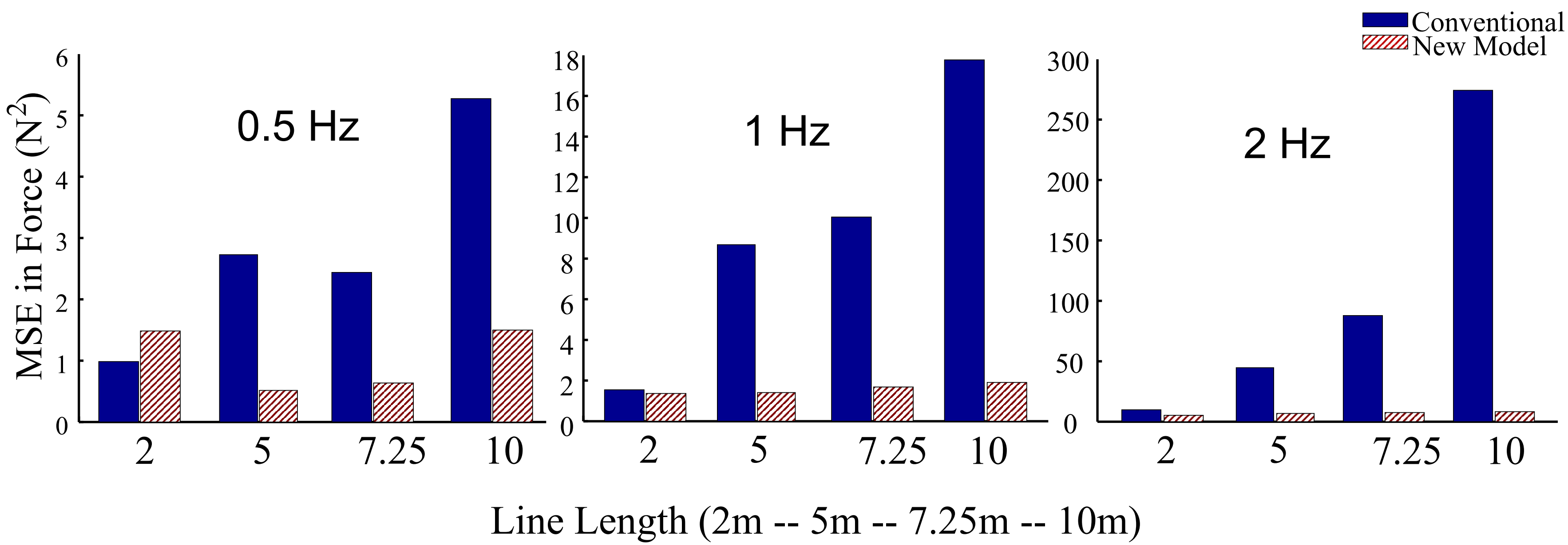
$$\dot{L} \leq 0 \quad if \quad k_1 \leq \bar{h}/2\varepsilon_1 + 1/2\bar{h}\varepsilon_2, \quad k_2 \leq \varepsilon_1/2 + \varepsilon_3/2$$

$$\varepsilon_1, \varepsilon_2, \varepsilon_3 > 0$$

RESULTS

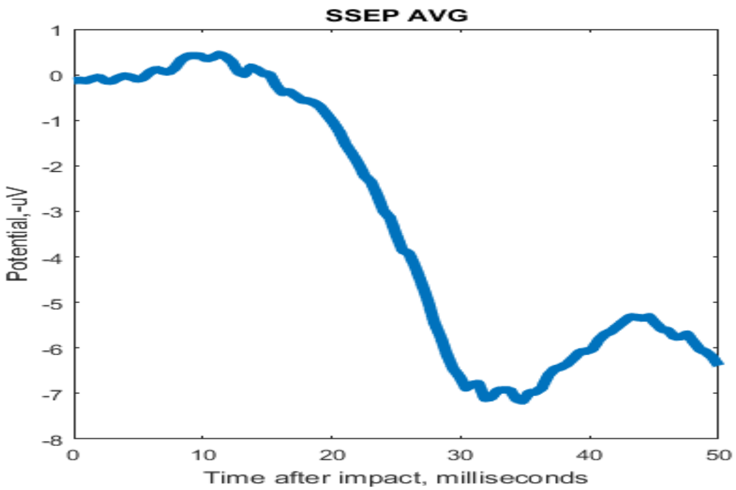
- Significant improvement at high frequency (1-2 Hz)
- Limited degradation in the performance as the frequency rise
- Improvement is marginal when the line length and the actuation frequency is low

$$F_{V_d} = F_P + \frac{\lambda_1 e_1 + \dot{F}_{e_d} + G_1}{\bar{h}} + k_1 s_1$$

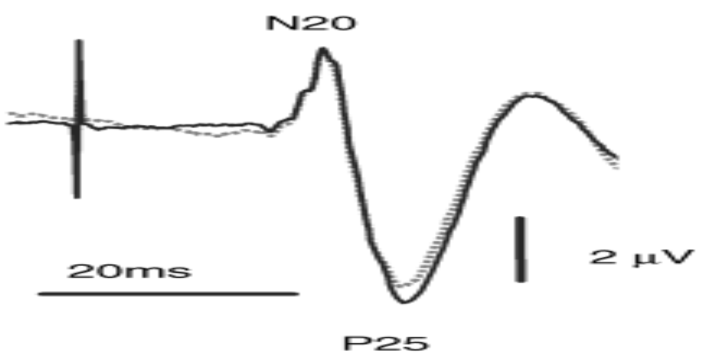


Melih Turkseven and Jun Ueda, Model Based Force Control of Pneumatic Actuators with Long Transmission Lines, *IEEE /ASME Transactions on Mechatronics, Conditionally accepted*

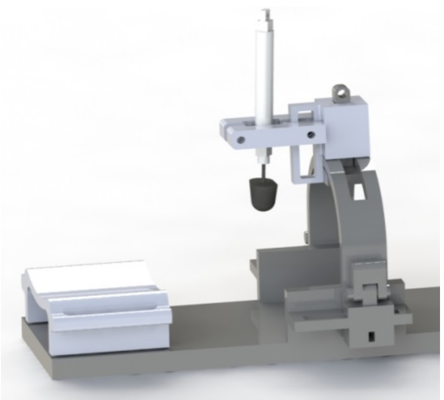
DISPERSION IN SENSORY SYSTEM OR MOTOR SYSTEM?



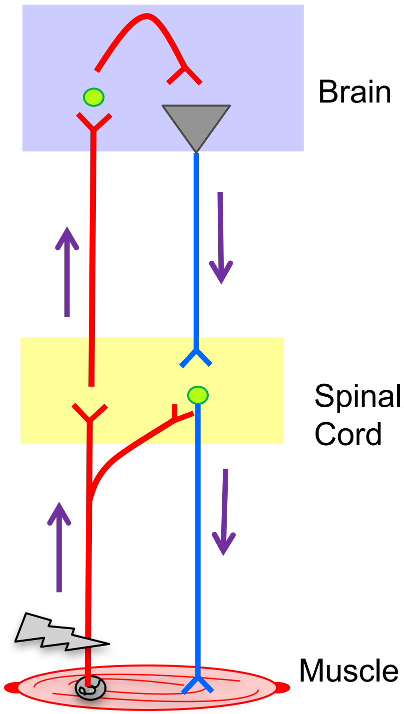
Preliminary results (single subject, 125 trials)
Delayed and widened P25 peak
Mechanical stimulation to FCR muscle



Wolters et al. (J. Physiology, 2005)
Single subject, 1000 trials
Electrical stimulation of the median nerve

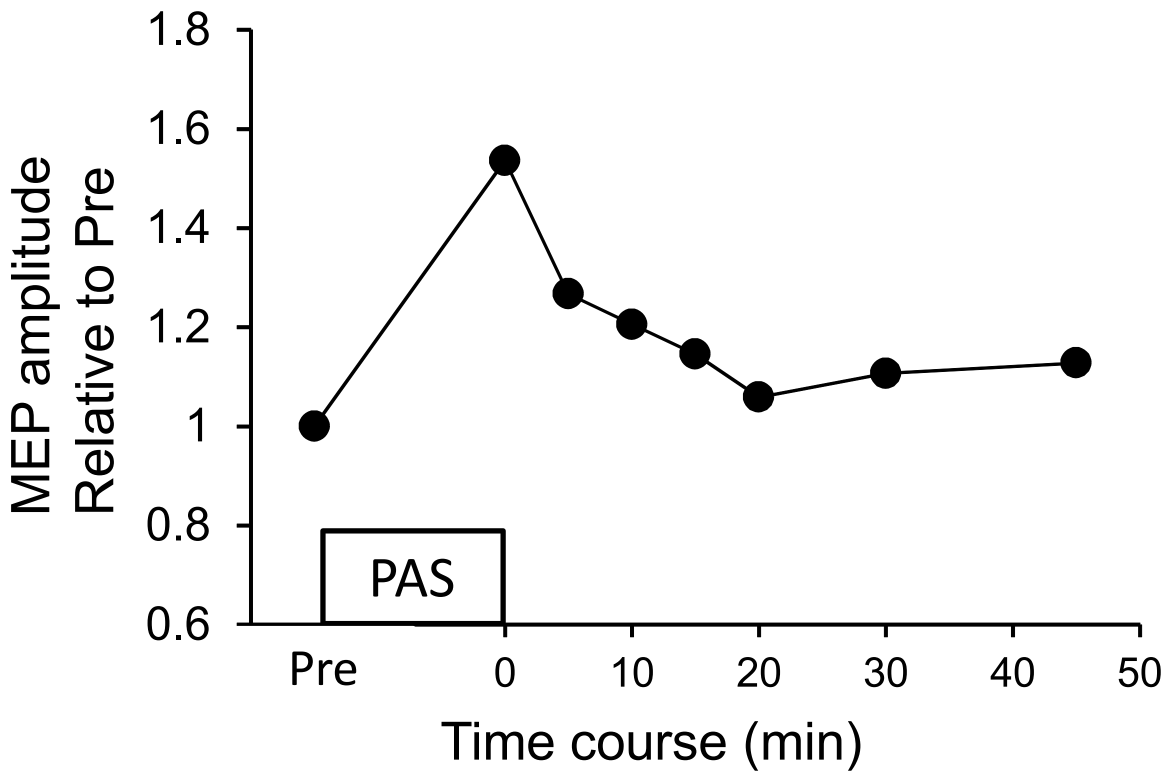


Mechanical Stimulation (tendon tapping)



PAS-INDUCED LTP

- LTP induced by mechanical (robotic) stimulation
- An example for potentiated MEP in a wrist flexor after PAS with mechanical stimuli compared with Pre in one subject.



RESPONSE TIME IS DIFFERENT FROM PERSON TO PERSON

Georgia Tech

Timing difference between mechanical stimulation command and TMS(ms)

Subject

	685	690	695	700	705	710	715	720	725	730	735	740	745	750	755	760	765	770	775	780	785	790	795	800	805
subject1	0	0	0	0	0	0	0	0	0	0	0	0	5	4	5	4	5	10	6	6	8	5	10	7	4
subject2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	6	6	3	2
subject3	0	0	0	0	0	0	0	0	0	0	3	4	2	1	0	1	0	1	0	0	0	0	0	0	0
subject4	0	0	3	3	3	1	2	4	8	4	5	0	0	1	0	0	0	0	0	0	0	0	0	0	0
subject5	0	0	0	3	9	2	1	2	1	4	7	5	5	3	2	3	2	3	5	2	1	0	0	0	0
subject6	0	0	1	1	2	4	6	2	6	4	6	4	7	6	6	4	5	2	4	6	4	4	3	2	0
subject7	0	0	0	0	0	0	3	5	4	1	0	3	1	0	0	0	0	0	0	0	0	3	0	4	9
subject8	0	0	0	0	0	0	5	2	1	1	2	3	3	2	2	2	6	3	3	2	1	2	3	5	2
subject9	0	0	0	0	0	0	9	7	10	10	8	8	7	10	6	6	7	7	5	8	2	10	6	5	4
subject10	0	0	0	0	2	2	3	5	8	9	9	9	6	3	3	5	4	6	2	1	5	3	3	0	0
subject11	0	0	0	0	0	5	4	2	9	8	5	3	1	0	0	1	0	0	0	0	0	0	0	0	0

	810	815	820	825	830	835	840	845	850	855	860	865	870	875	880	885	890	895	900	905	910	915	920	925	930
subject1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject2	0	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject6	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject7	10	10	10	9	10	10	10	10	10	9	5	5	5	7	6	5	6	5	0	6	3	3	1	1	0
subject8	5	6	3	4	7	2	5	2	10	4	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject9	4	7	0	8	7	3	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
subject11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

SCALE
0
1
2
3
4
5
6
7
8
9
10

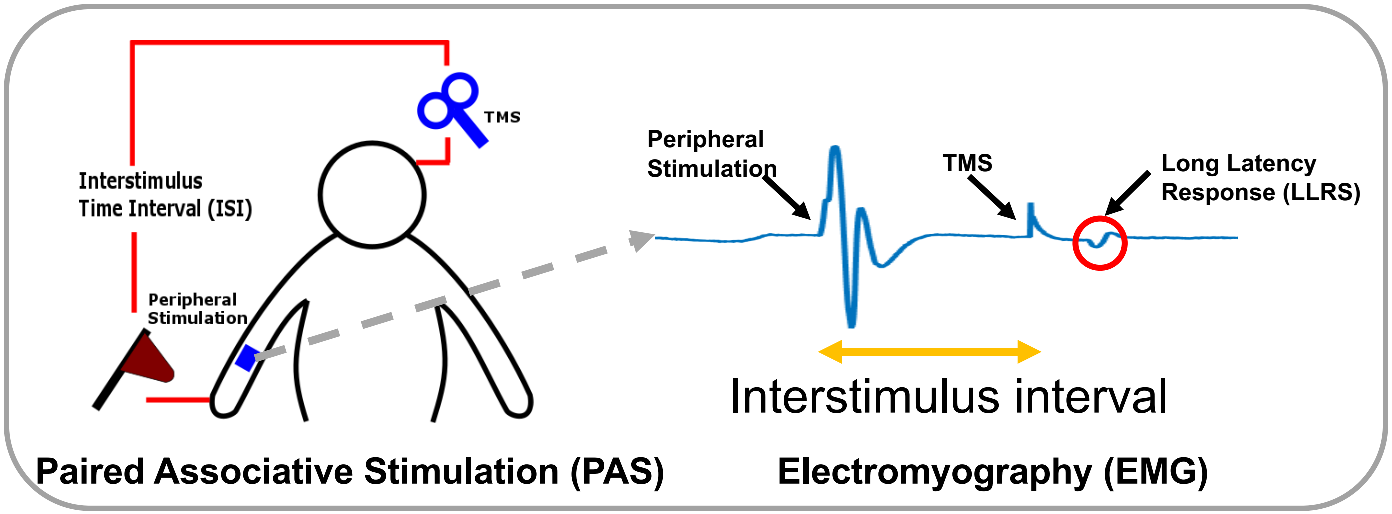
*** Each subject has different time range that shows long latency response.**

*** Numbers(0~10) represent the number of long latency response out of 10 trials.**

Large individual differences → Machine learning

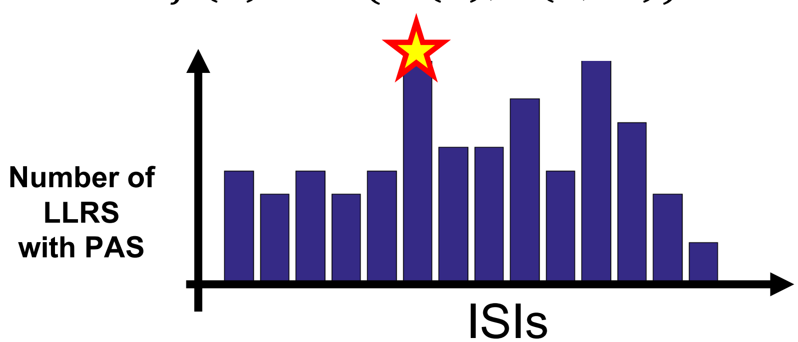
BAYESIAN ESTIMATION OF NEUROMODULATION

How to find the “optimal” interstimulus interval in dividable subjects



Bayesian optimization

$f(x) \sim GP(m(x), k(x, x'))$



Algorithm

1: $for\ t = 1,2, \ldots$

2: $x_t = argmax_x U(x|D_{1:t-1})$

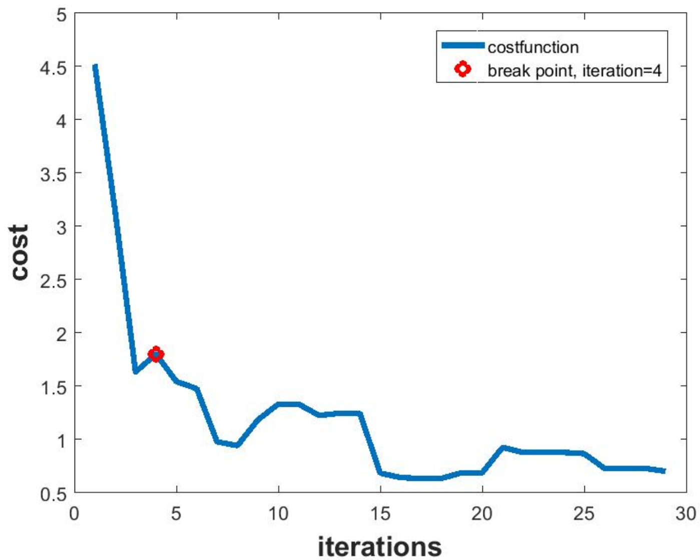
3: $y_t = f(x_t)$

4: $D_{1:t} = \{D_{1:t-1}, (x_t, y_t)\}$

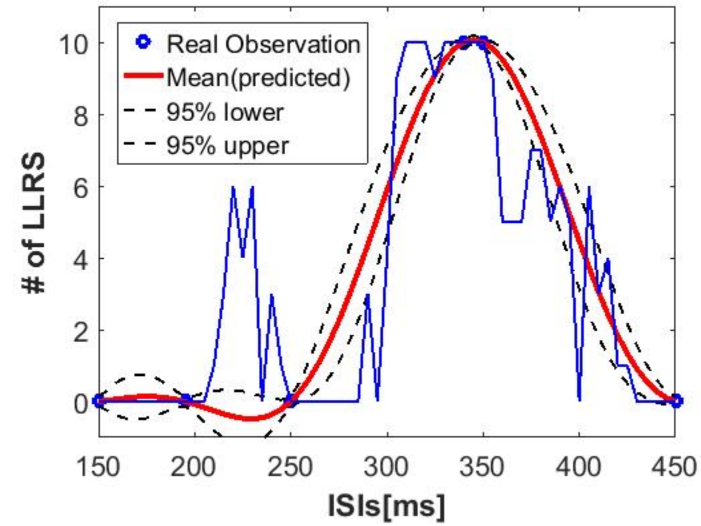
5: $Update\ GP$

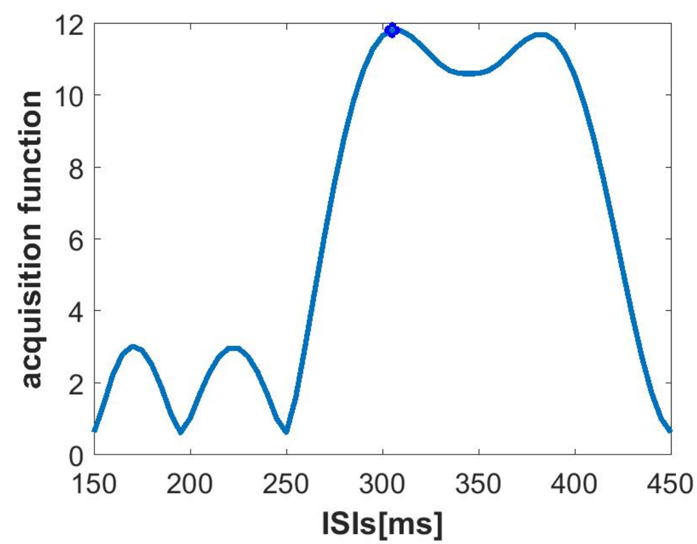
6: $end\ for$

BAYESIAN ESTIMATION RESULTS



4th Iteration





- Acquisition function : Upper Confidence bound selection criterion

$$GP - UCB(x) = m(x) + \kappa * \sigma(x)$$

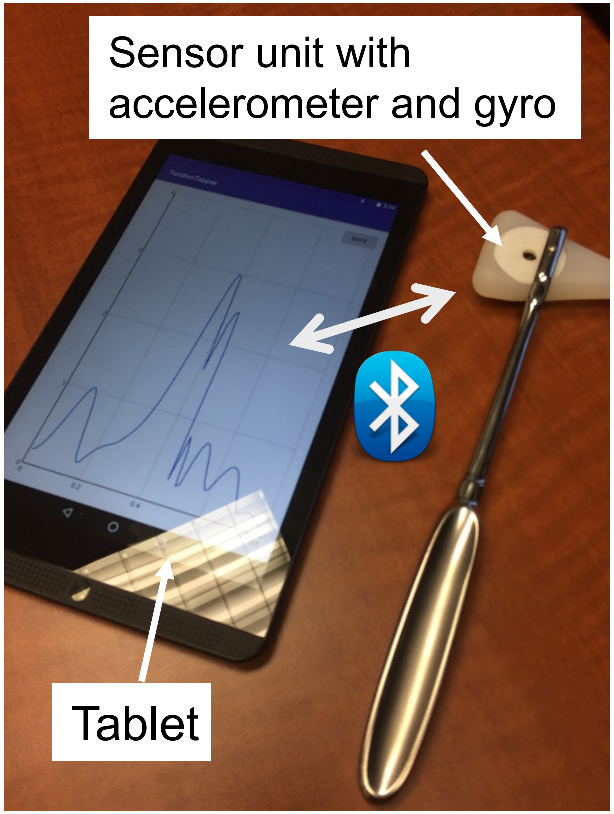
- Kernel Function : Squared exponential kernel

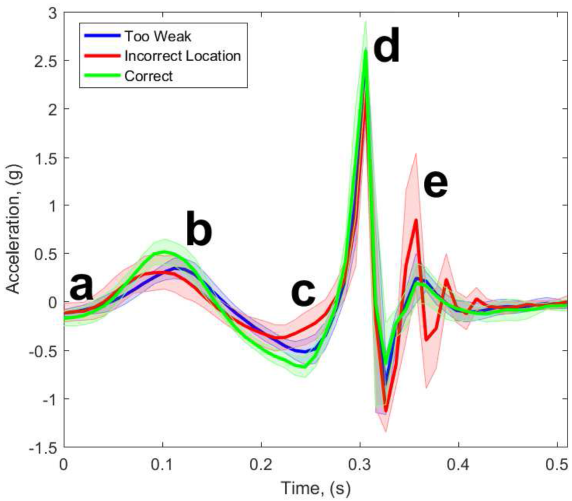
$$k(x, x') = e^{-\frac{1}{2}(x-x\prime)^2}$$

- Cost Function

$$cost = \sum \frac{(estimated\ time\ window - true\ time\ window)^2}{200}$$

IOT MEDICAL HAMMER





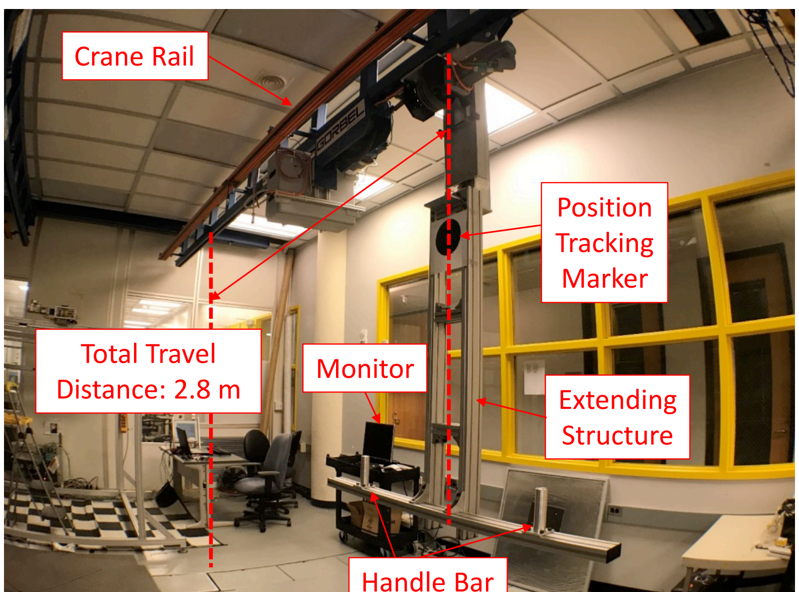
Data Scope	Correct	Correct Location	Correct, NS	Correct Location, NS
A Only	95.1%	85.4%	96.5%	**90.97%**
B Only	91.7%	72.9%	91.6%	**73.61%**
Both	86.4%	75.7%	86.11%	**73.96%**

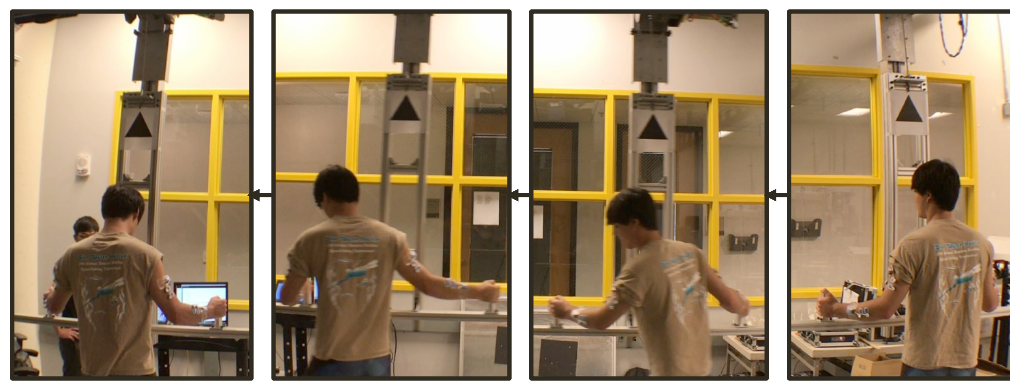
Meinhold and Ueda, An Instrumented Medical Hammer with Diagnostic, Therapeutic and Pedagogical Applications, ASME DSCC 2017

ROBOT-ASSISTED BIMANUAL TASKS

- Human modes in robot-assisted assembly

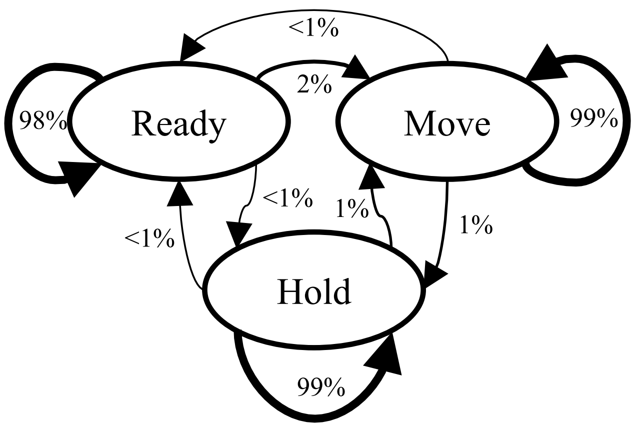
Factory GM Flint Assembly

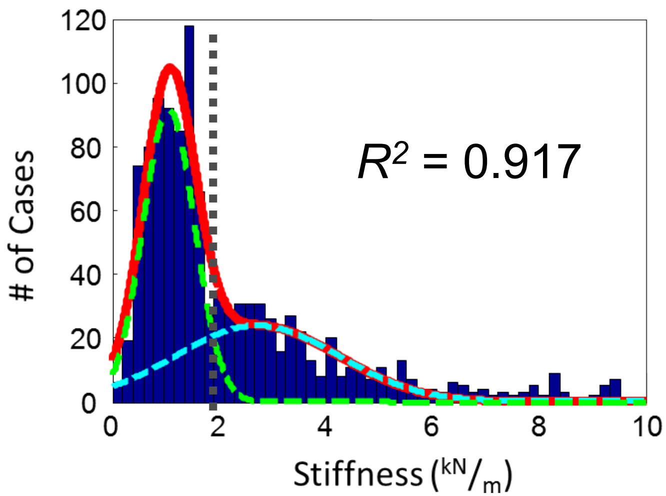


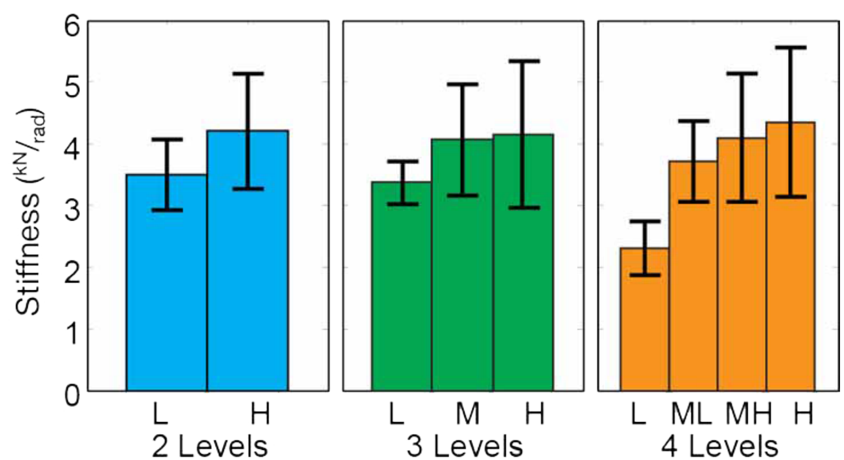


VARIABILITY IN HUMAN STIFFNESS

Muscle stiffness: stochastic parameter in the system



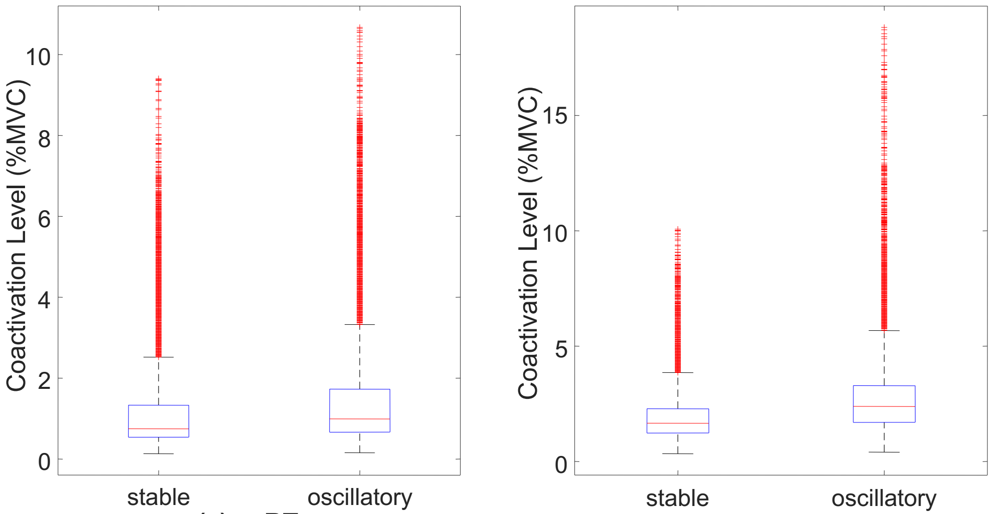




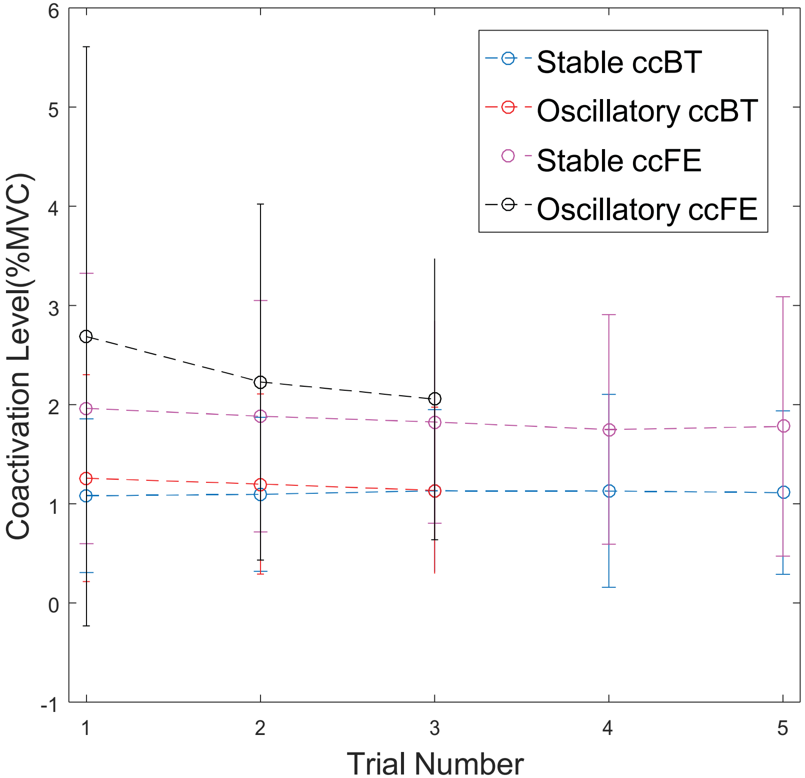
VARIABILITY IN HUMAN STIFFNESS (CONT.)

Muscle stiffness

- Greater co-contraction in oscillatory environment
- Adaptation



(a) ccBT (b) ccFE

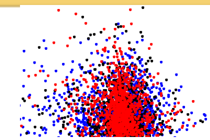


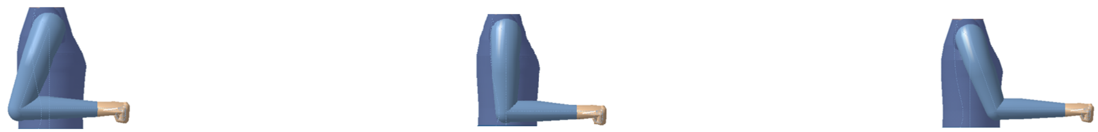
Pluckter, Moualeu, Ueda, *IEEE Transactions on Robotics,* 2017, *submitted*

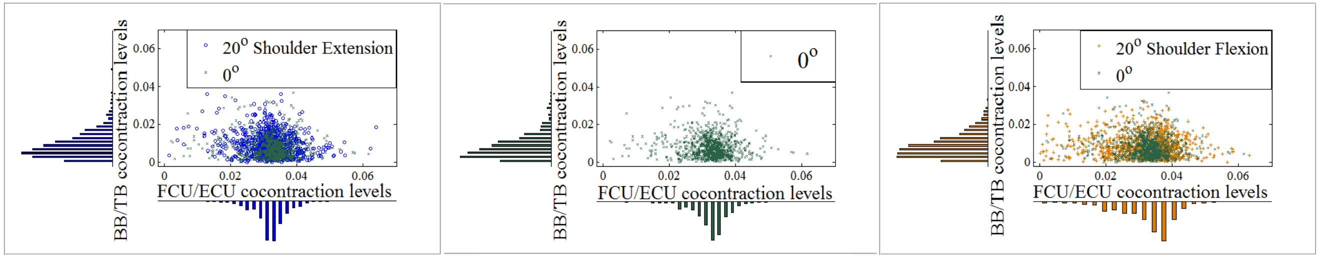
MODELING OF MUSCLE COCONTRACTION

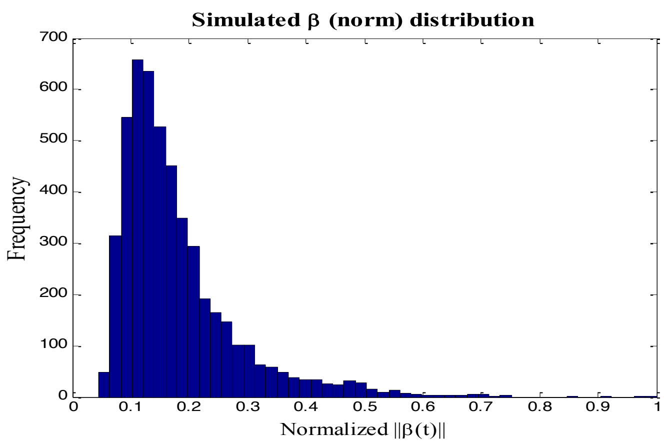
$$f = f_0 + (I - A^+ A)\underline{\beta}$$

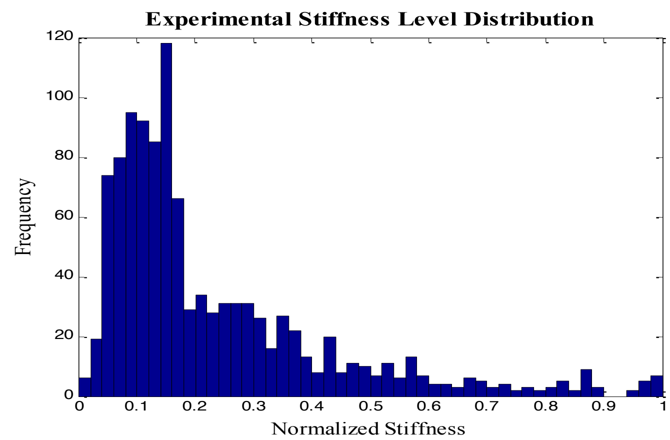
Cocontraction
(random variable)











Antonio Moualeu
ME, PhD

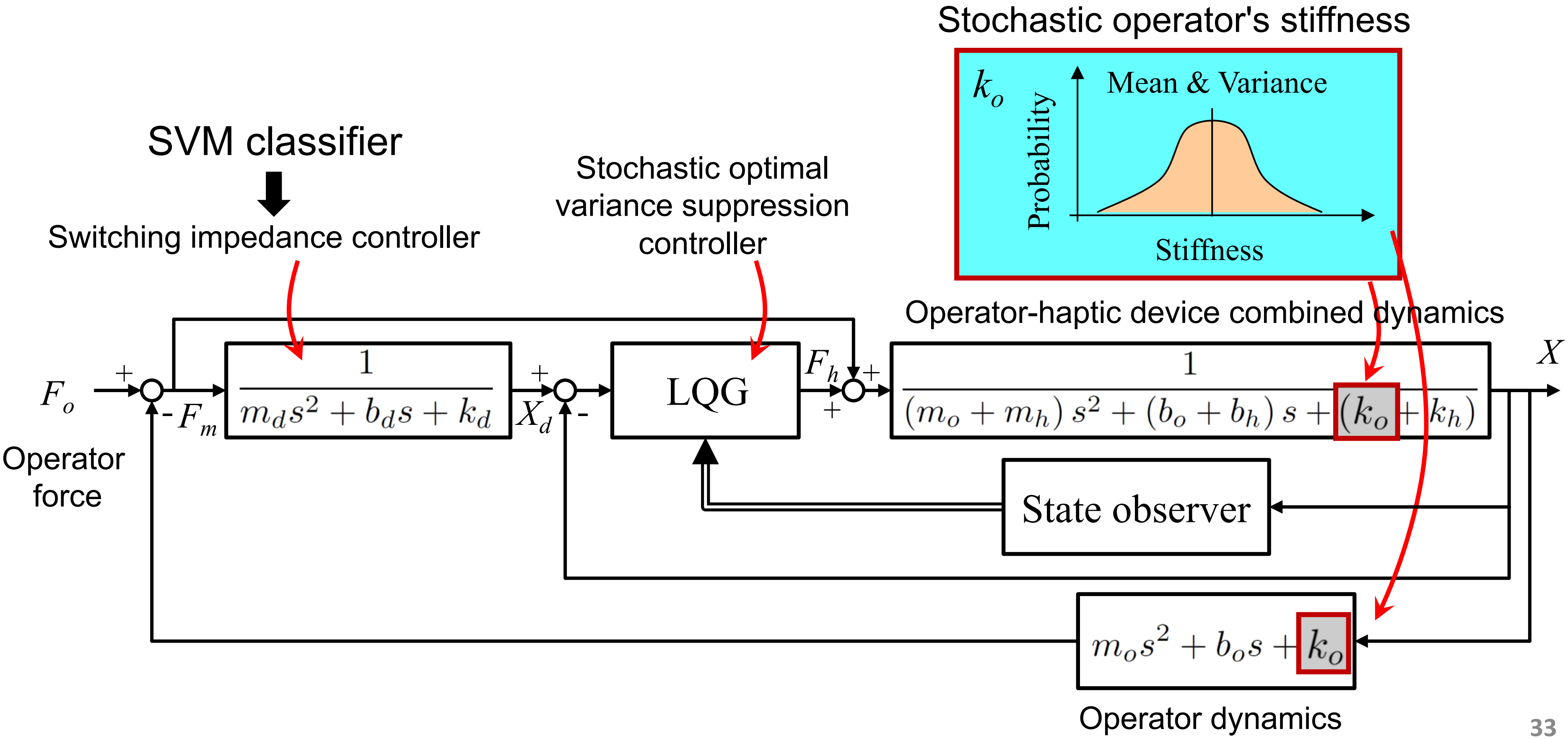
<u>Simulation:</u> Analysis of 5000 data points obtained from all simulations suggests that the <u>distribution is not normal</u> ($p < 0.001$).

<u>Experiment:</u> Stiffness distribution obtained from four (4) subjects.

Moualeu and Ueda, *IEEE IROS* 2014

PROPOSED STOCHASTIC CONTROLLER

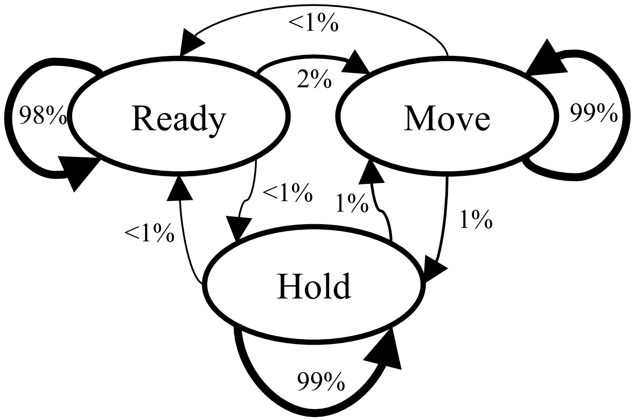
- SVM based stiffness classifier
- Switching impedance control for force assisting
- Stochastic LQR

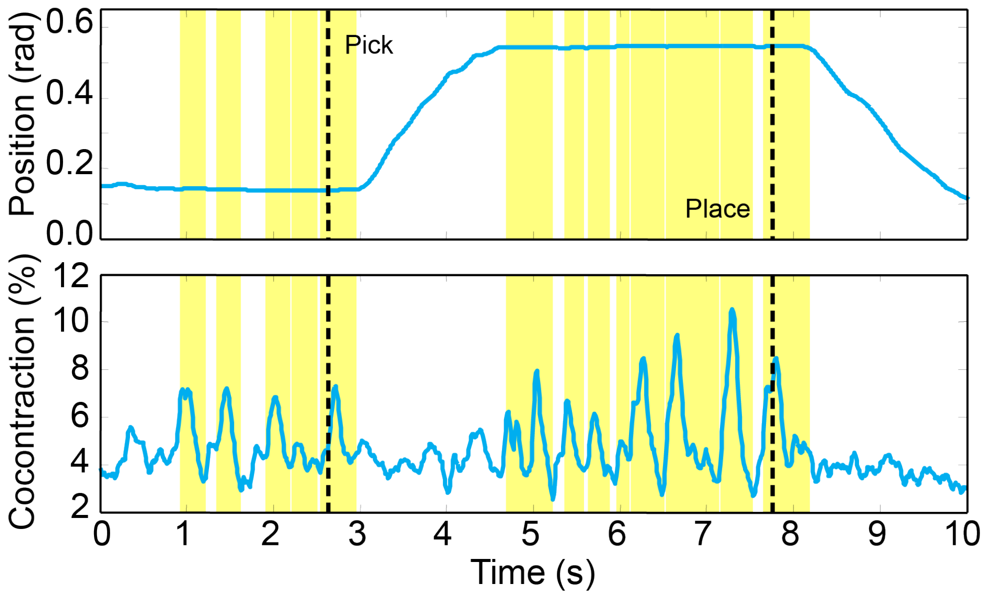


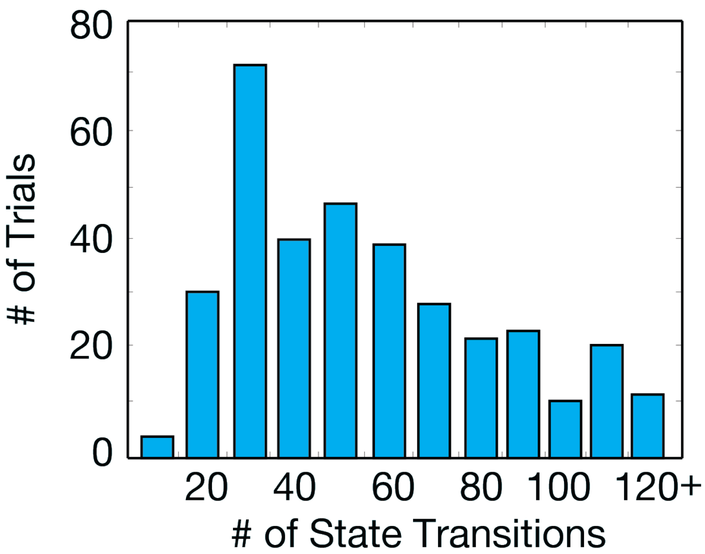
OSCILLATION IN HUMAN-ROBOT "HYBRID" SYSTEM

Excessive chatter between states

Fundamental problem of assistive robotics based on "human effort" <u>measurement</u>

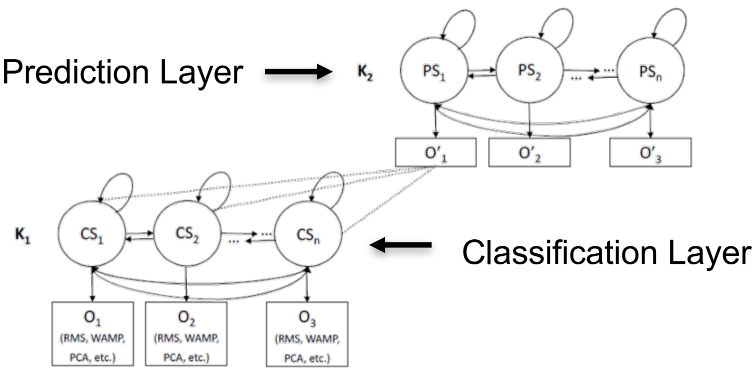






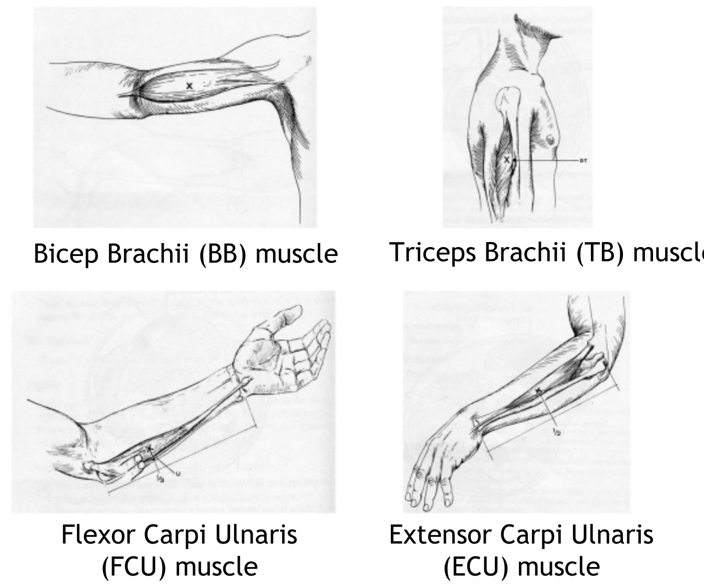
Gallagher, Gao, and Ueda, *Advanced Robotics*, 2014

INTENTION ESTIMATION FROM GAZE AND CO-CONTRACTION



Layered Hidden Markov Model

- sEMG: measurements of electrical signals from muscles
- Useful for endpoint stiffness estimation



Cocontraction Muscle Groups [2]

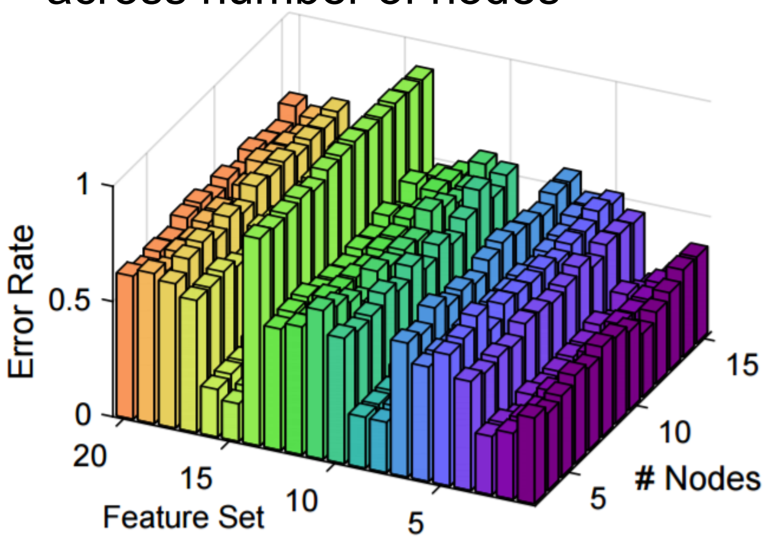
- Properties:
    - Modular
    - Quick to Train
    - Use of Markov Assumptions

Yosef Razin, Kevin Pluckter, Jun Ueda, Karen Feigh, "IEEE Robotics and Automaton Letters (RA-L), 2017

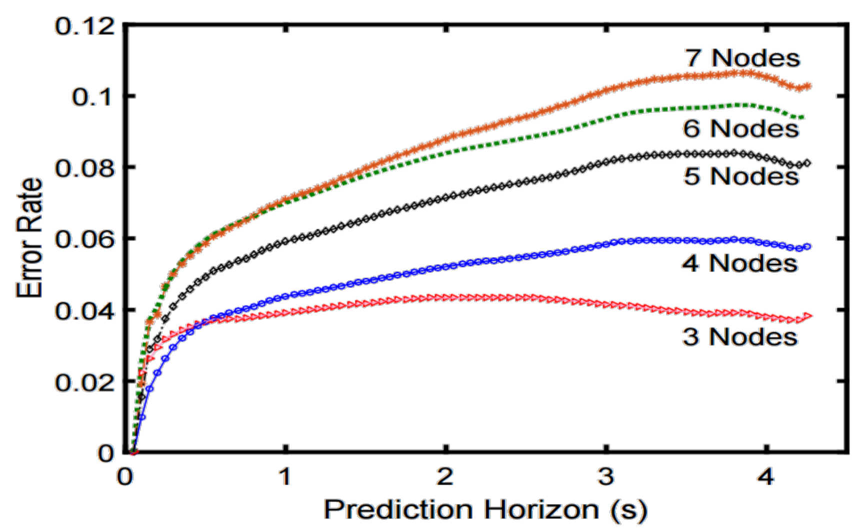
LHMM SETTINGS

- Best feature sets included 3-d.o.f. force readings and EMG data
- Worst feature sets were missing 3-d.o.f. force readings or included extra EMG features
- Minimal performance difference across number of nodes

- Prediction Layer Performance over time vs. number of nodes
- Performance Ranking switch for 3 and 4 nodes at 50 ms



Feature Set vs. Number of Nodes vs. Error Rate



Number of Nodes vs. Error Rate

INTENTION ESTIMATION RESULTS

- Novel haptic device operator intent prediction algorithm
  - Better classification performance than many other algorithms

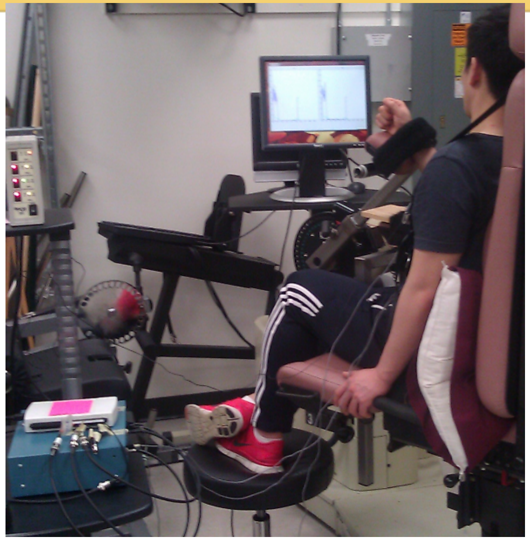
Classification Ranking for Performance of LHMM vs. Other Learning Algorithms

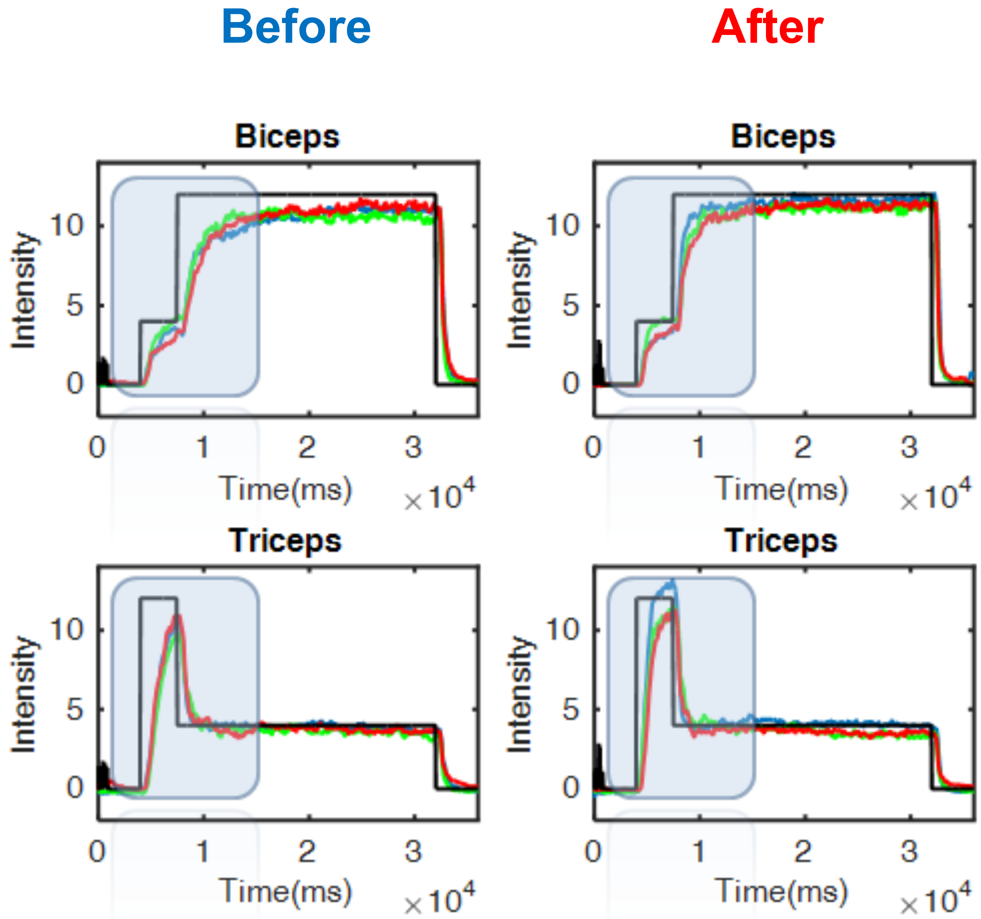
Rank	Method	Features	Error	Precision	Recall	F1
1	LHMM	FS #10	0.159	0.762	0.780	0.735
10	DT	E (10-PC)	0.229	0.686	0.687	0.685
11	NB	FS #13	0.242	0.681	0.654	0.659
15	QDA	FS #9	0.275	0.660	0.623	0.621
29	SVM	FS #9	0.332	0.611	0.518	0.453
39	LDA	FS #9	0.347	0.522	0.512	0.484
50	KNN	FS #23	0.363	0.532	0.536	0.532

  - Full system accuracy up to 82% with 50 ms window

Yosef Razin, Kevin Pluckter, Jun Ueda, Karen Feigh, “IEEE Robotics and Automaton Letters (RA-L), 2017

CO-CONTRACTION TRAINING





Co-contraction: Two muscles practice
Contraction : single muscle practice
Control: No practice

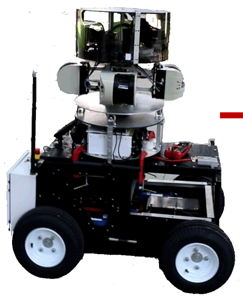
Ahmar NE, Shinohara M. Slow intermuscular oscillations are associated with cocontraction steadiness. Medicine & Science in Sports & Exercise, 2017

DEXTEROUS TELEOPERATION FOR DISASTER RELIEF (DOD-MOTIE)

Hybrid Site Sensing and Human-multi-robot Team Collaboration for Disaster Relief at Nuclear Power Plants

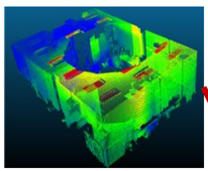
Semantically enriched as-built damaged site visualization

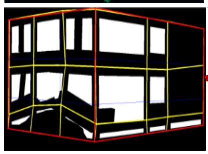
GT Cho



Ground Robot for Mapping Infrastructure (GroMI)

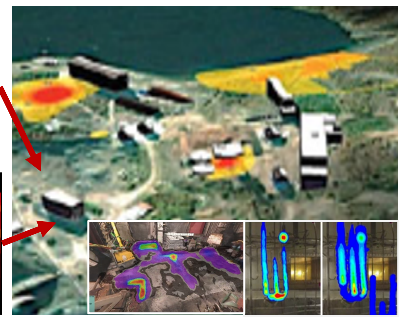
Thermal/radiation point cloud





Damaged structure modeling

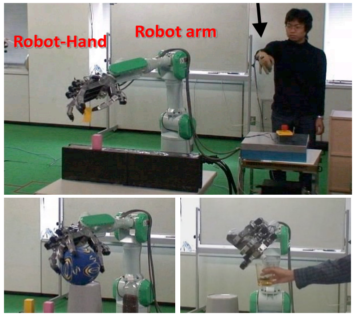
3D Radiation intensity map

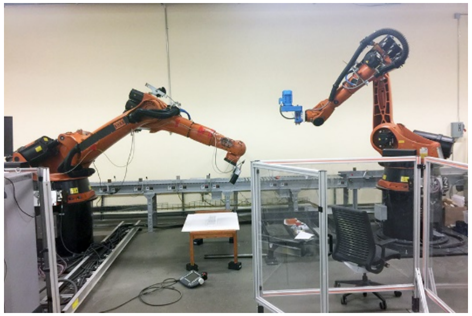


Radiation images

Shared-control of a multi-DOF dexterous hand-arm system with adaptive gain scheduling

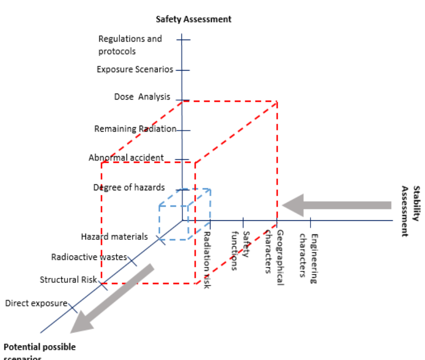
GT Ueda





Dexterous hand manipulation and integrated hand-arm system

Risk assessment and response strategies



Likelihood	Consequence: 1 Insignificant	2 Minor	3 Moderate	4 Major	5 Catastrophic
A Almost Certain	11	16	20	23	25
B Likely	7	12	17	21	24
C Possible	4	8	13	18	22
D Unlikely	2	5	9	14	19
E Rare	1	3	6	10	15

HYU Ahn

Update priority areas to focus

Assessment of the impact of the operational system with respect to task performance and cognitive burden

Remotely controlling multiple unmanned excavator robots

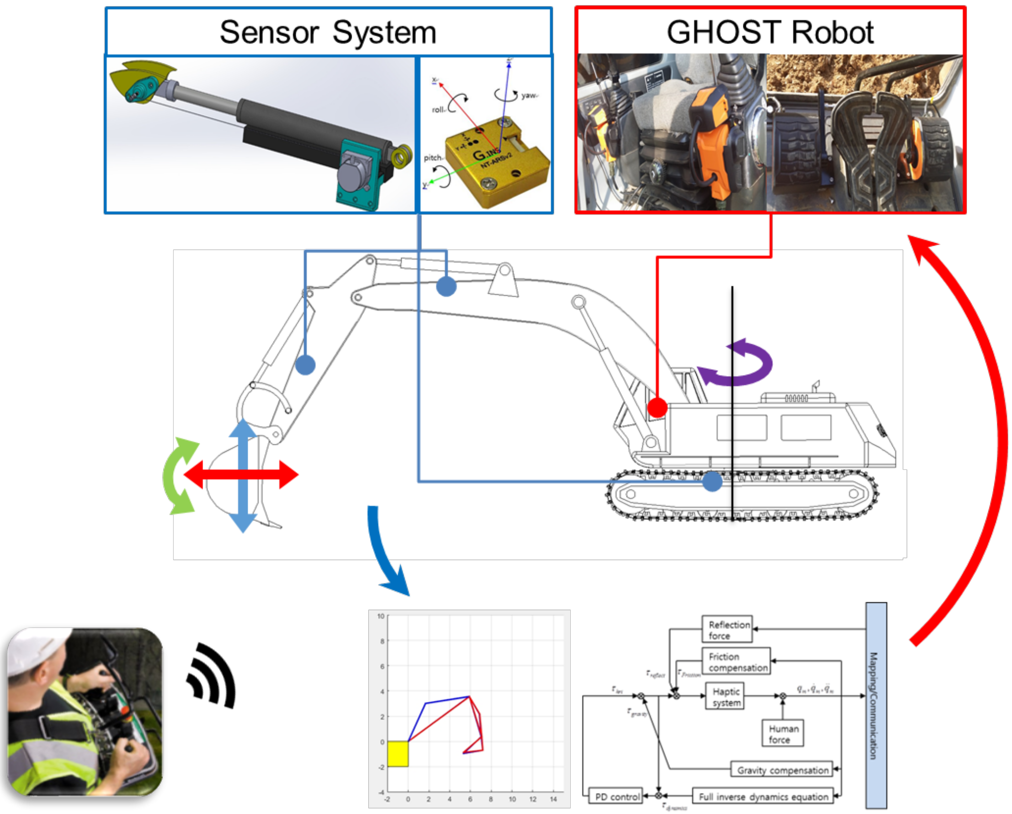
HYU Han

UNMANNED EXCAVATOR

Georgia Tech

Unmanned Relief/Restoration Robot using Promptly Renovated Excavator

- Retrofit unmanned tele-operation robot into commercial excavator
- Control strategy for the unmanned relief/restoration robot



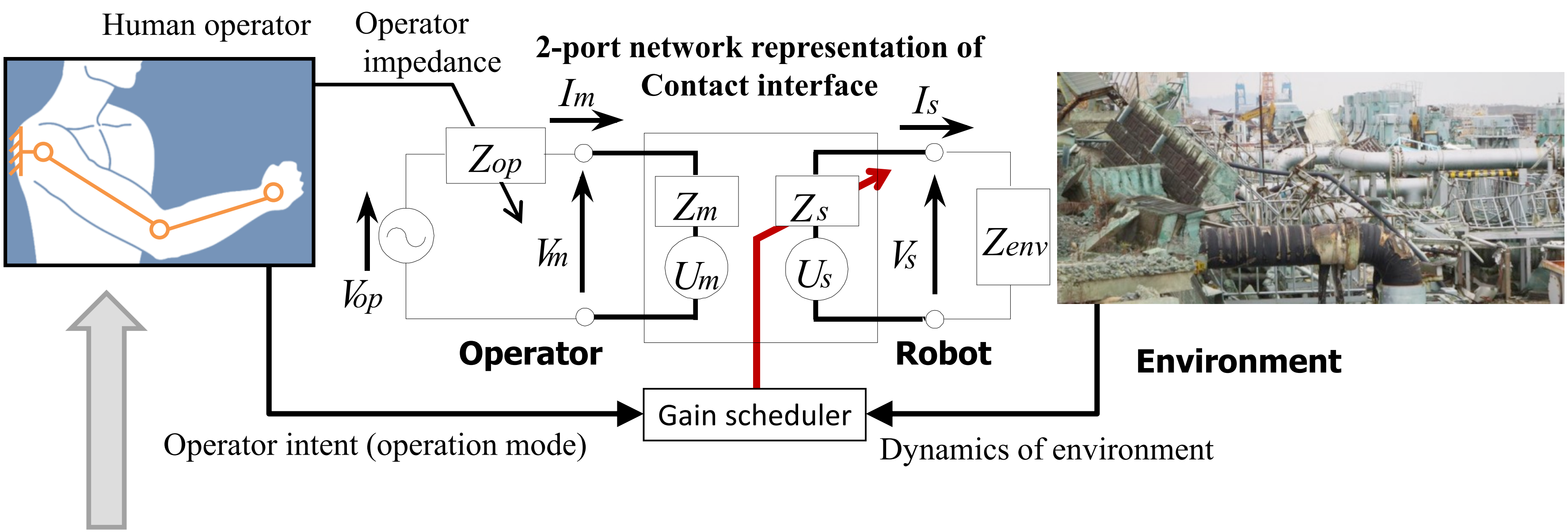
Configuration of unmanned relief/restoration robot

Installation type robotic manipulator for the unmanned excavator

Dr. Han, Robotics Laboratory, Hanyang University at Erica.

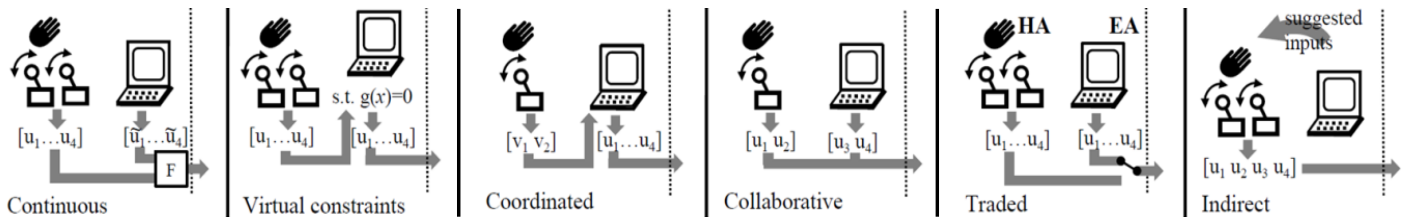
ADAPTIVE GAIN SCHEDULING FOR ROBUST TELE-OPERATION (UEDA-GT)

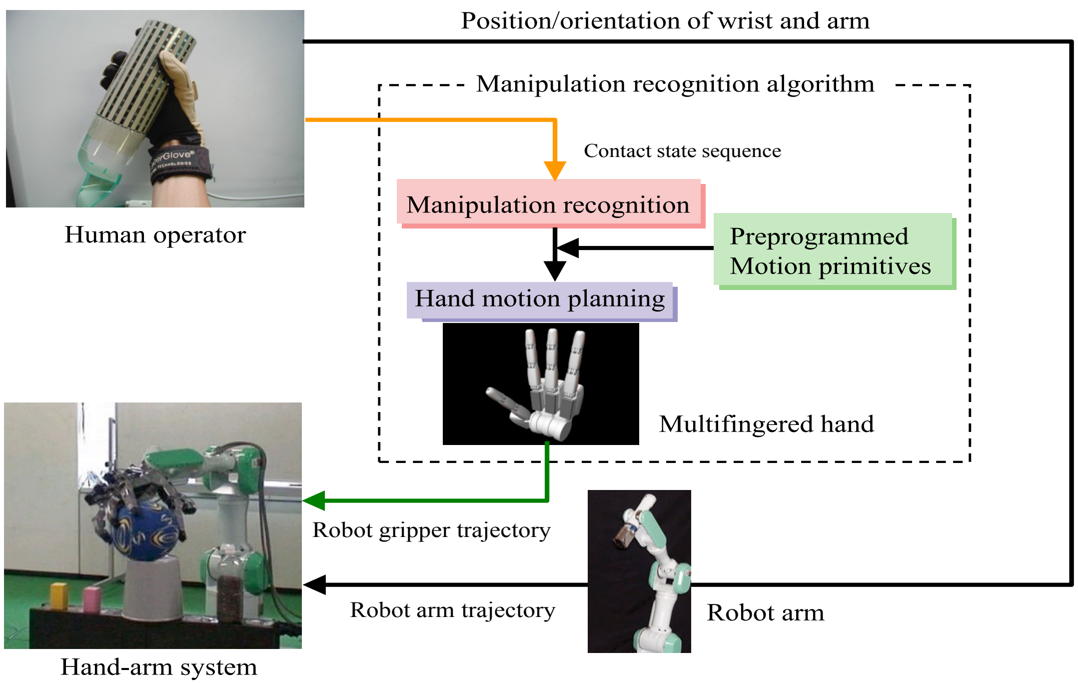
To utilize the dynamics of the environment and intent of the operator, to adjust the controller gains and maintain appropriate, stability margins, to balance the performance and stability.

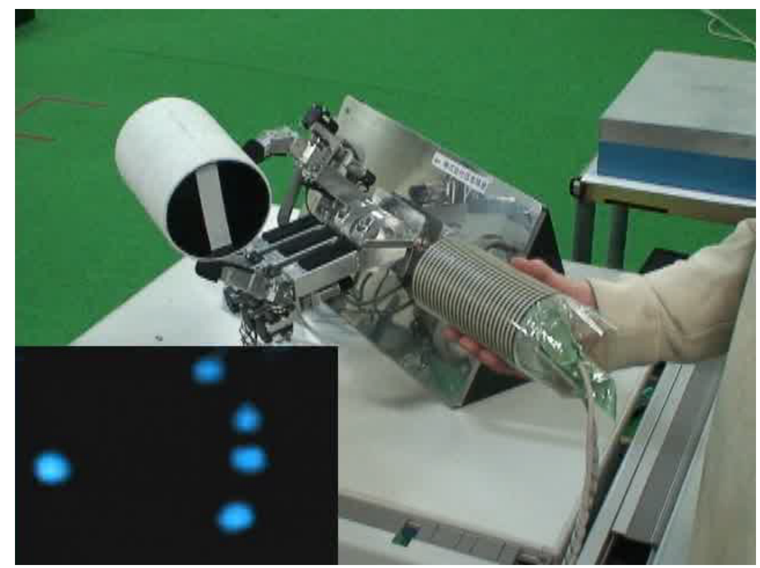


Operator as a stochastic system (muscle contraction, cognitive mode…)

SHARED CONTROL FOR SCALED HAND-ARM TELE-OPERATION

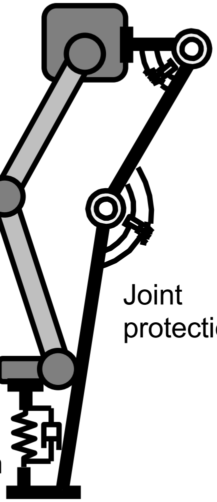






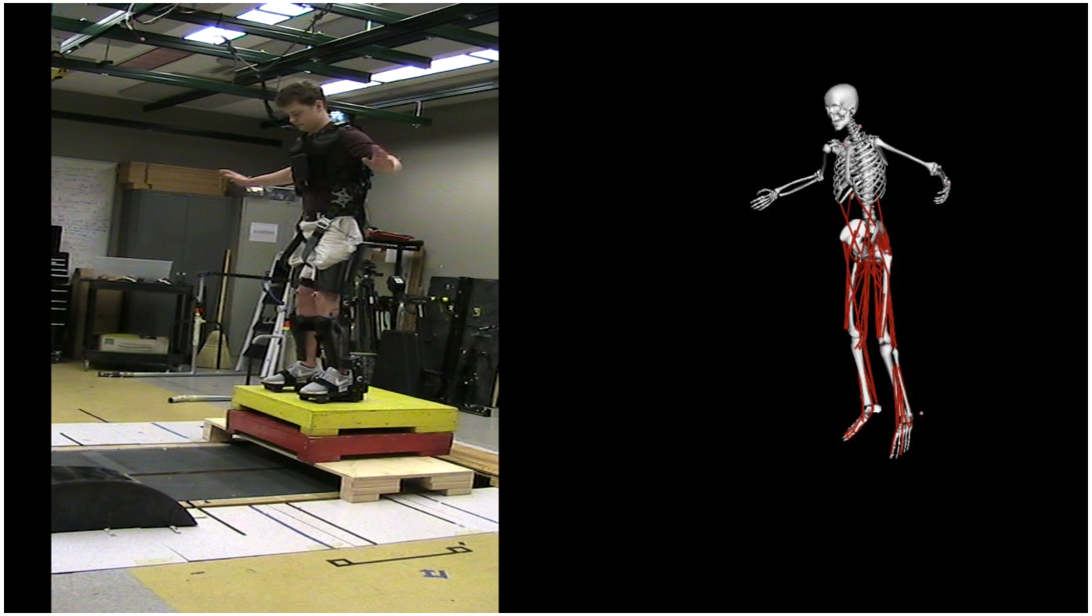
Ueda, Kondo, Ogasawara, *Mechanism and Machine Theory*, 2010

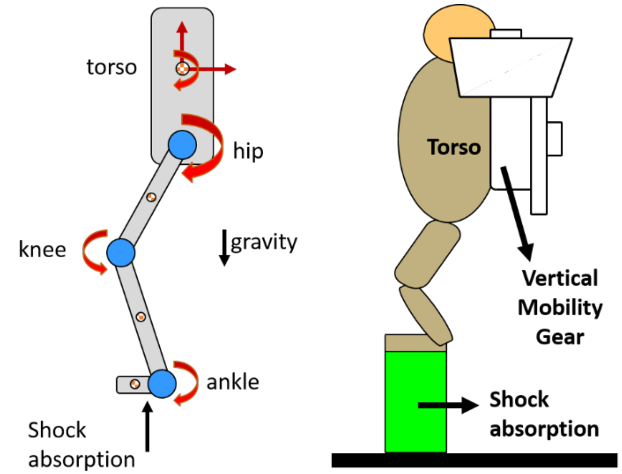
JETPACK

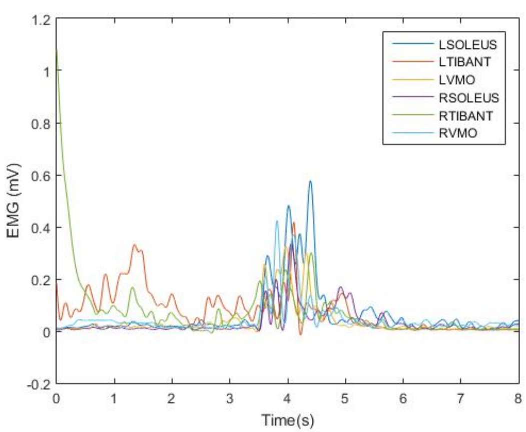


Michael Mayo, GTRI
@ Jetpack Aviation

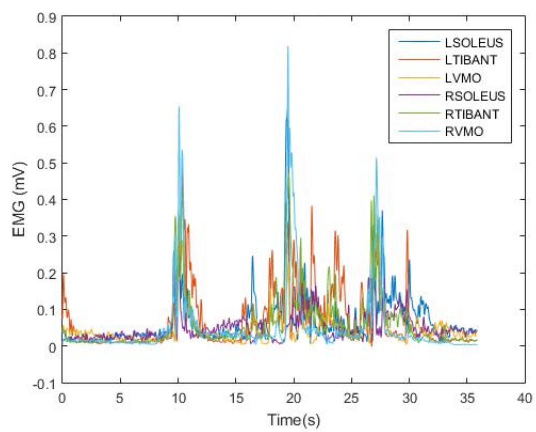
BODY PROTECTIVE EXOSKELETON





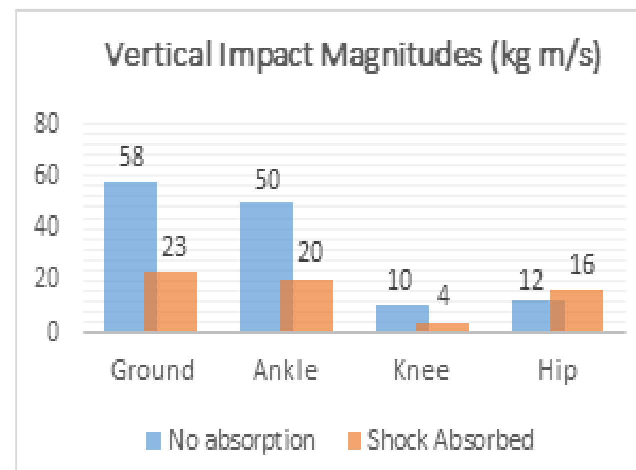


With exoskeleton



Without exoskeleton

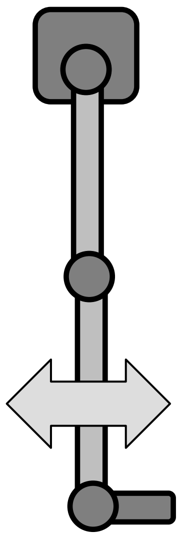
Muscle activity (EMG) measurement



Dynamic falling simulation

How to protect lower limb

Muscle and tendon injuries



Excessive joint
movements

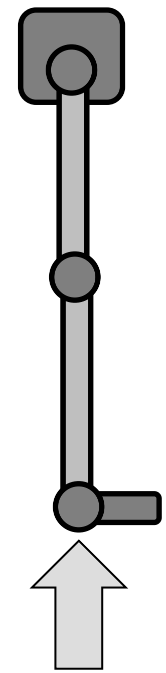
Admissible motion space

“orthogonal” to each other

⊥

⊥

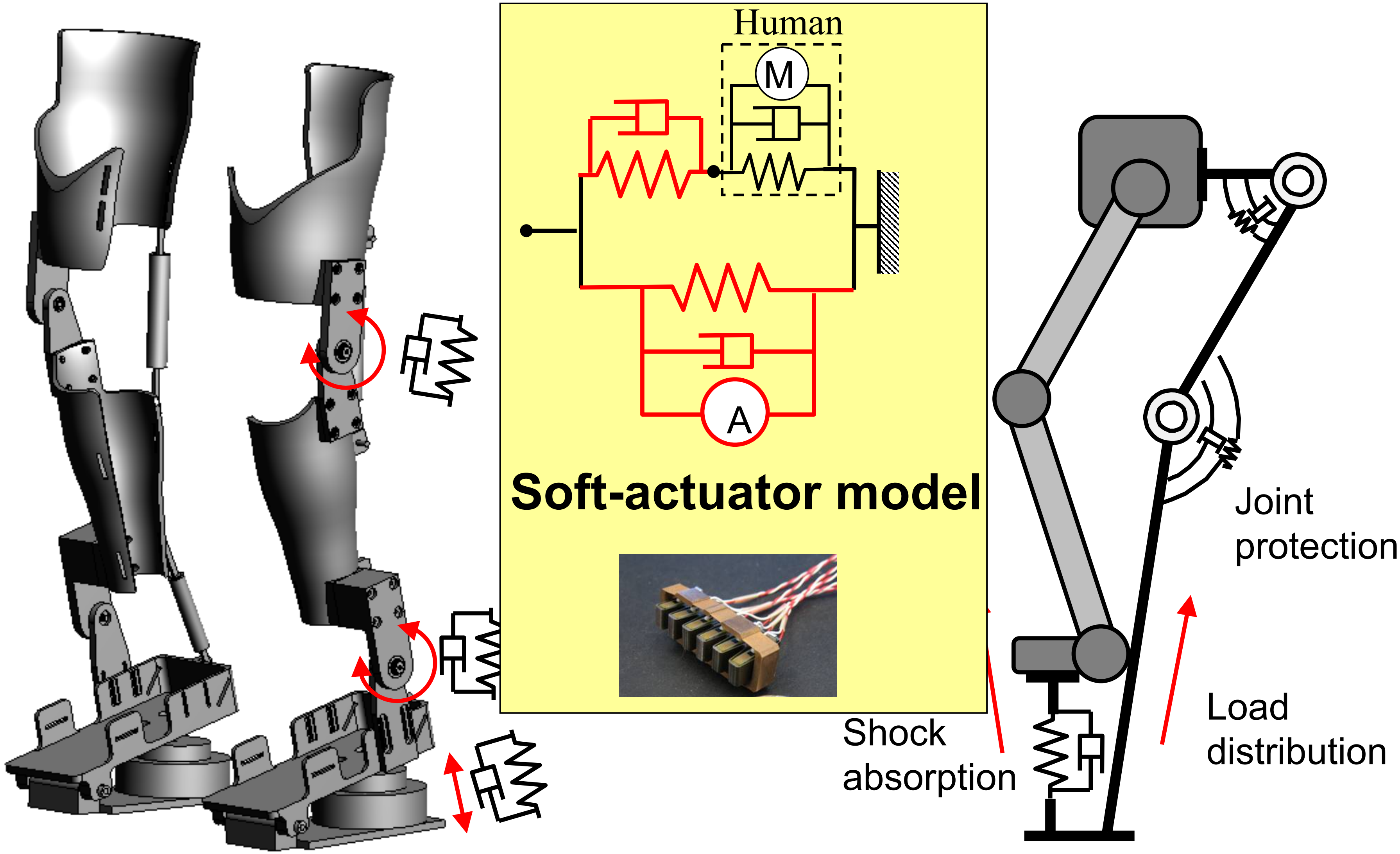
Bone and cartilage injuries



Excessive pressure
to bone/cartilage

Constrained motion space

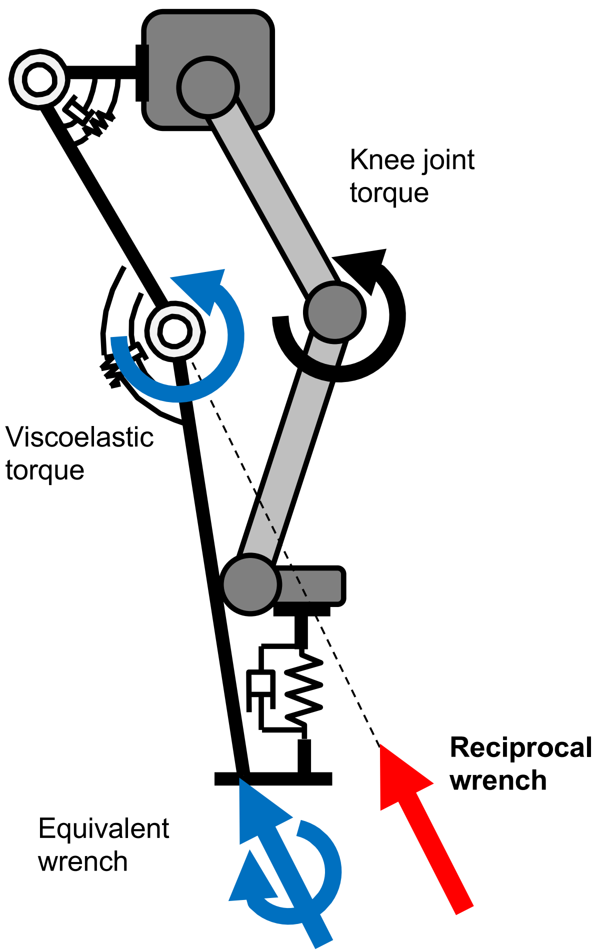
Series and parallel connection of mechanical shock absorbers



CLASSIFICATION OF EXOSKELETON FUNCTIONS

Georgia Tech

Reciprocal screw theory



Condition* 1: *Protection of bones and joints: External shock forces must be in the constrained motion space of the exoskeleton structure (i.e., reciprocal wrenches) and must be in the admissible motion space of the human skeleton (i.e., non-reciprocal wrenches), ideally orthogonal to each other

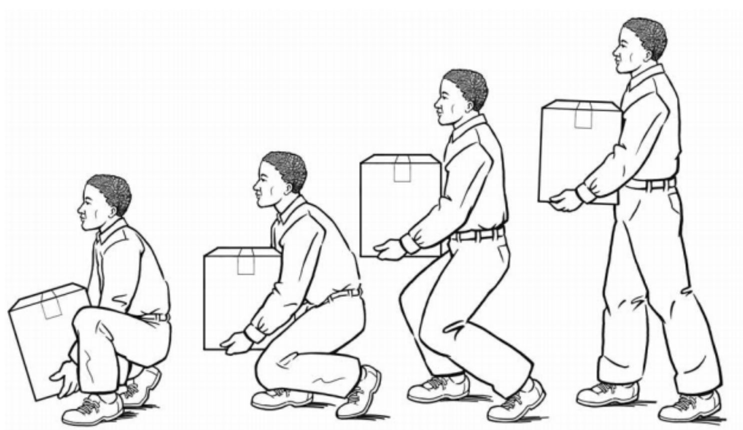
Condition* 2: *Protection of muscles: Equivalent joint efforts of external shock forces and viscoelastic forces from shock absorption elements must be non-orthogonal in the joint space, ideally parallel to each other

Condition* 3: *Impact and shock reduction to the entire system: External shock forces and equivalent viscoelastic forces from shock absorption elements must be non-orthogonal in the task space.

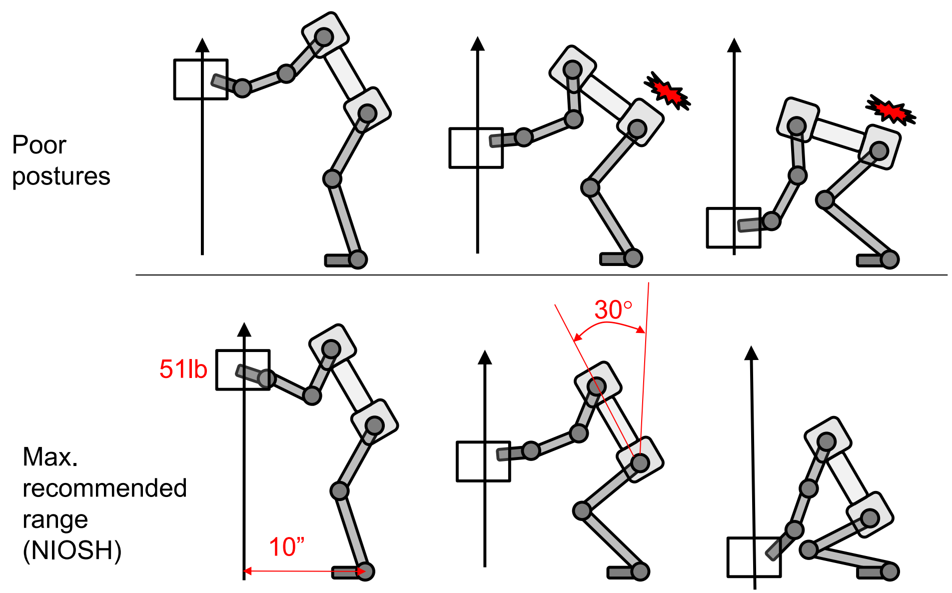
Condition* 4: *Force augmentation: Equivalent wrenches of muscle forces and robot actuation efforts must be non-orthogonal to each other in the task space, ideally parallel to each other, and must not be in the constrained motion space of either of the systems.

WEARABLE ROBOT FOR CONSTRUCTION WORKER SAFETY

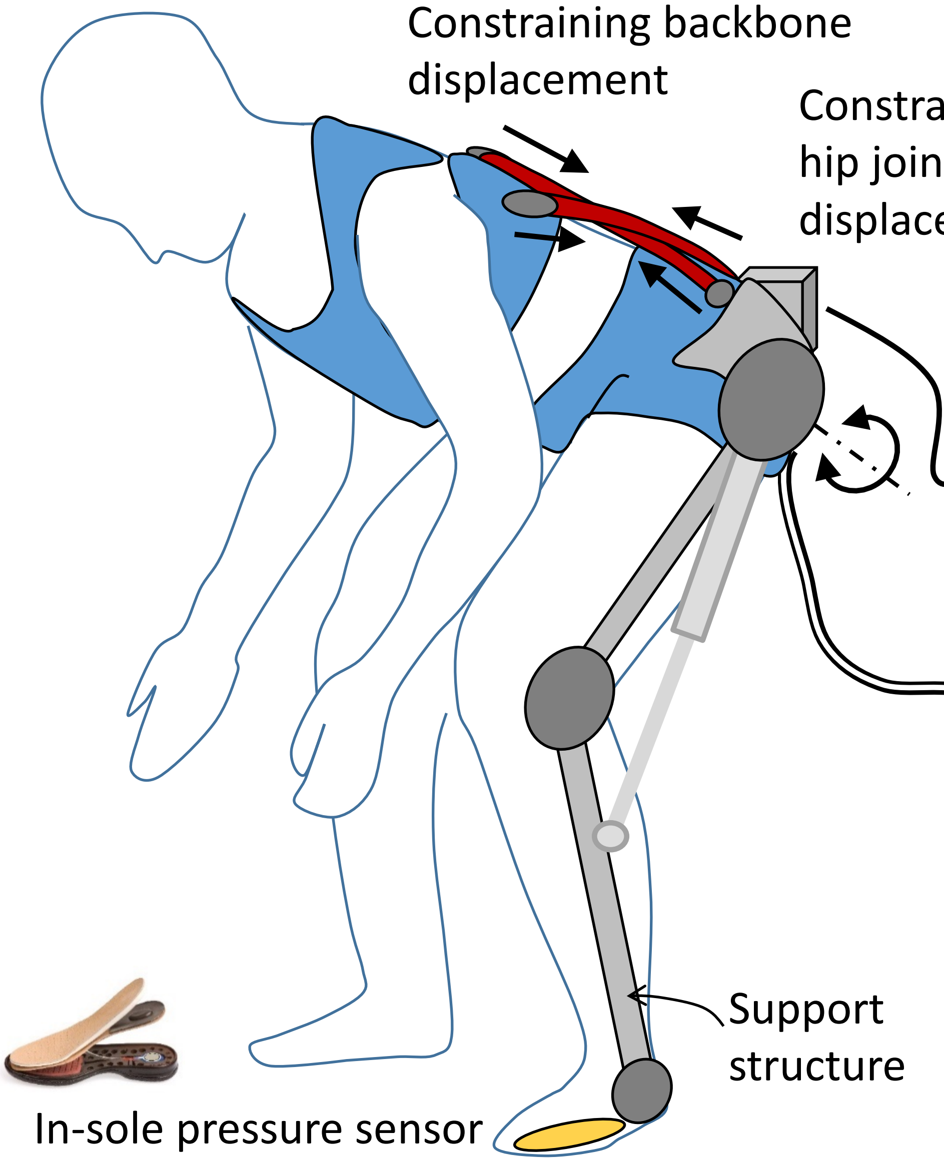
- **Goal:** Assisting masonry workers to enhance the safety through the integration of automated activity & posture analysis and exoskeleton technology.
- **Specific Objectives**: To develop a smart robotic exoskeleton which provides workers:
  1) Physical constraints to decrease the risk of back injuries
  2) Strength assistance as long as the posture is in the safe range.



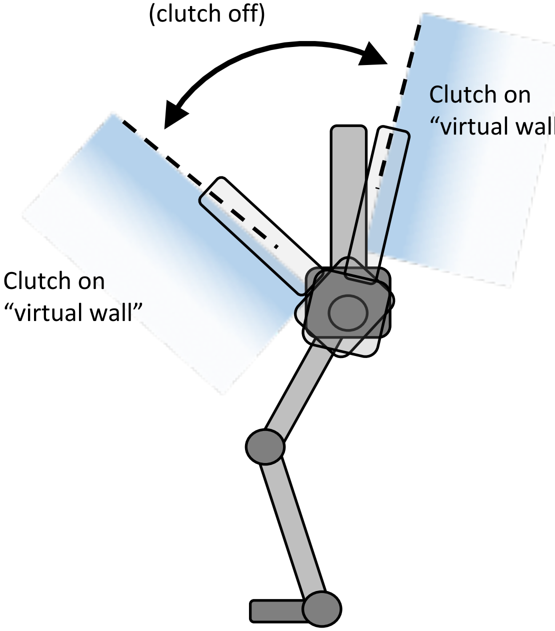
Best Practice by NIOSH



PROPOSED PNEUMATIC EXOSKELETON SYSTEM



In-sole pressure sensor



Portable air sources

CDC/NIOSH….

Georgia Tech

https://blogs.cdc.gov/niosh-science-blog/2016/03/04/exoskeletons/

CDC Centers for Disease Control and Prevention
CDC 24/7: Saving Lives, Protecting People™

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Aging Workers

Wearable Exoskeletons to Reduce Physical Load at Work

Posted on March 4, 2016 by Brian D. Lowe, PhD, CPE; Robert B. Dick, PhD, Captain USPHS (Ret.); Stephen Hudock, PhD, CSP; and Thomas Bobick, PhD, CSP, CPE

Photo courtesy of SuitX, US Bionics, Inc.

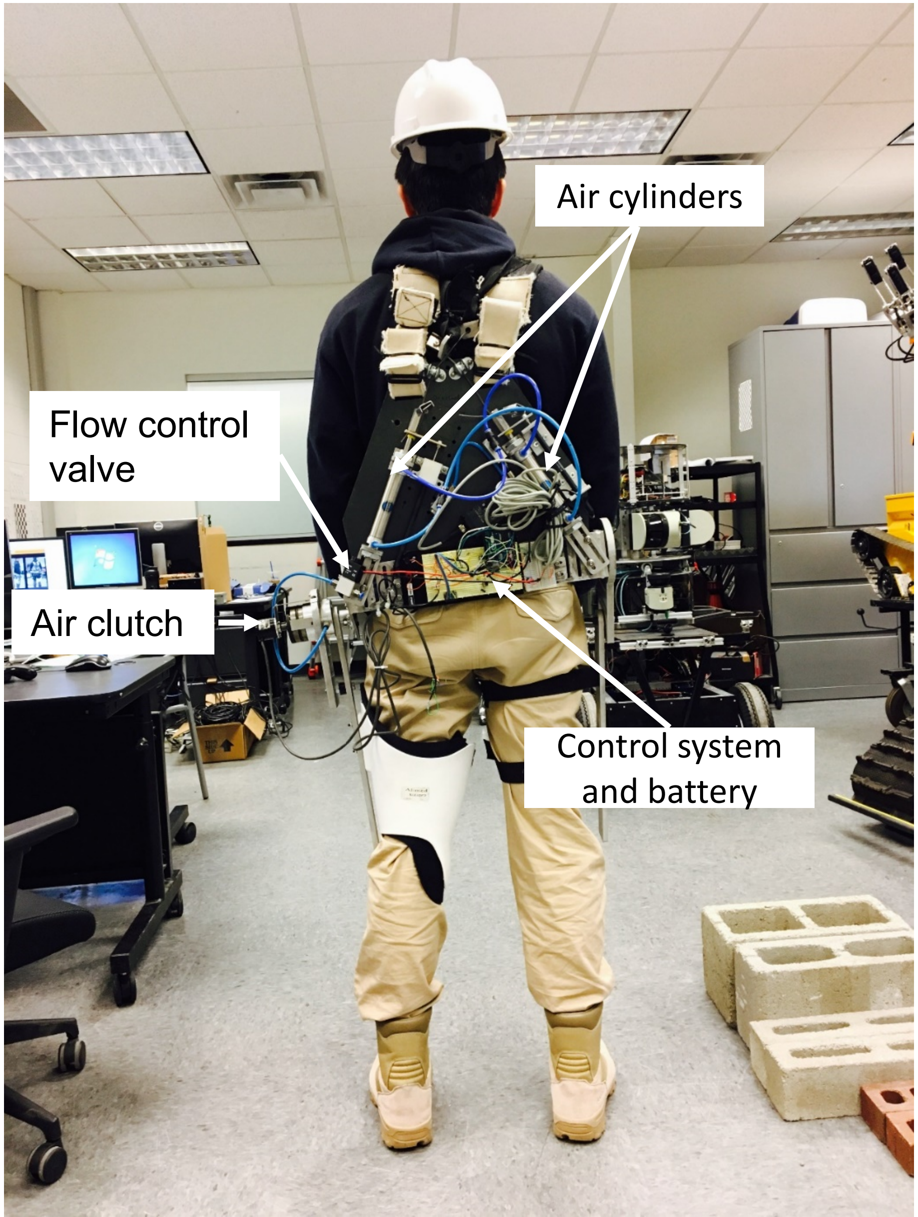
Robotic-like suits which provide powered assist and increase human strength may conjure thoughts of sci-fi and superhero film genres. But these wearable exoskeleton devices are now a reality and the market for their applications in the workplace is projected to increase significantly in the next five years. As with any technologic innovation some of the pros and cons and barriers to adoption are not completely understood. In this blog our objectives are to: (1) describe wearable exoskeletons in the context of workplace safety and health control strategies; (2) highlight current and projected trends related to industrial applications of these technologies; and (3) invite input from our stakeholders on workplace health and safety experiences, positive or negative, with these devices.

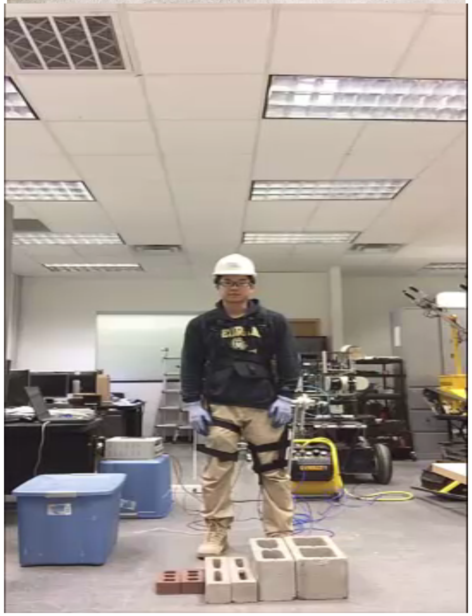
The **wearable exoskeleton** was defined by de Looze et al. (2015) as *"…a wearable, external mechanical structure that enhances the power of a person. Exoskeletons can be classified as 'active' or 'passive'. An active exoskeleton comprises one or more actuators that augments the human's power and helps in actuating the human joints. …A strictly passive system does not use any type of actuator, but rather uses materials, springs or dampers with the ability to store energy harvested by human motion and to use this as required to support a posture or a motion."* Passive systems require no external power and use springs, elastic cords, or other resilient elements to provide either a restoring moment that

risks before widespread workplace adoption. Some questions to address include, but are not limited to:

- Do some devices create a transference of load between musculoskeletal regions that still puts the worker at risk? For example, a vest or hip-supported device may transfer load off the arms and shoulders, but the increase in total load transferred to the spine and lower extremities may also have long term effects.
- Does the added weight of some devices increase energy expenditure/metabolic work load? Do some devices affect user comfort?
- Do some devices affect the balance of the wearer by changing their center of mass or increasing rate of fatigue in the lower extremity muscles? As reported by de Looze et al. (2015) increases in leg muscle activity have been reported for some devices (e.g. Barret and Fathallah, 2001; Ulrey and Fathallah, 2013); this may occur because the "external forces applied by the [exoskeleton] equipment needs to be counteracted to retain balance…". Can this increase in leg muscle activity contribute to lower extremity fatigue and increased risk for loss of balance? Correspondingly, are fall risks increased because of this possible leg fatigue and loss of balance?

EXOSKELETON FOR CONSTRUCTION SAFETY



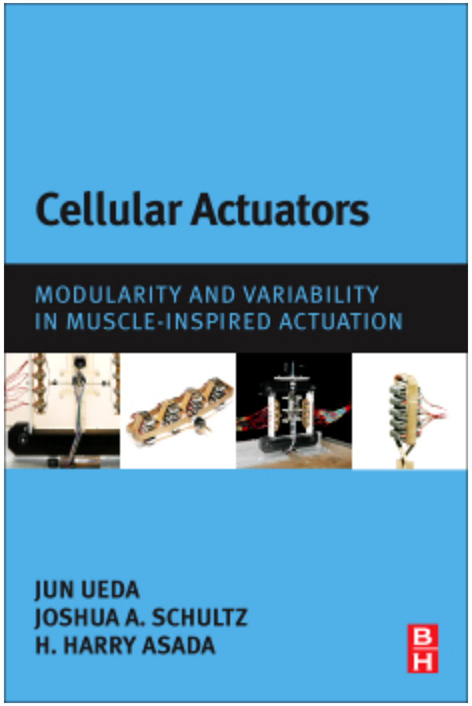


Applied physiology (motor control)

Exoskeleton

Force-assisting sy

Robo
and e



Ueda, Schulz, Asada
January 2017
Butterworth-Heinemann

Ueda & Kurita
Sep 2016
Academic Press

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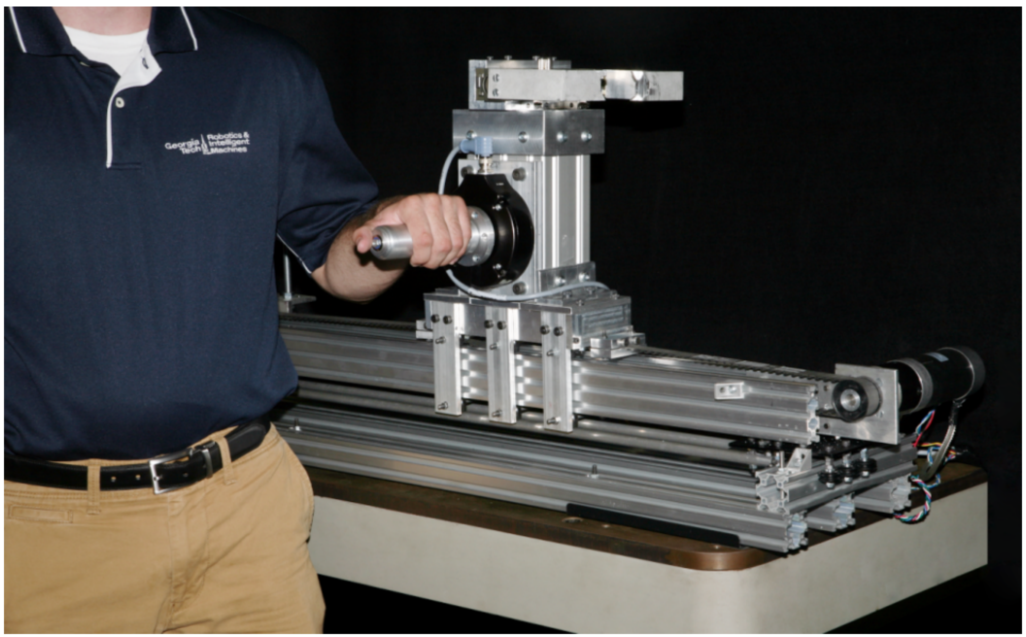
Teleoperation

Motion control

High-speed servoing

QUESTIONS?

CENTER FOR COMPACT AND EFFICIENT FLUID POWER
A National Science Foundation Engineering Research Center



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