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Scuola Superiore Sant'Anna

IROS 2018 Workshop on Controlling Soft Robots: Model-based vs. Model-free Approaches

Control strategies for soft robotic manipulators

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Abilities not yet reached by robots

Lessons from Nature: simplifying principles

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School of Advanced Studies – Pisa

Lessons from Nature: simplifying principles

Too complex?
Rather too simple?

Studying living organisms and understanding what makes their behavior so smart and efficient

In robotics, we need **simplifying principles** for control and behavior

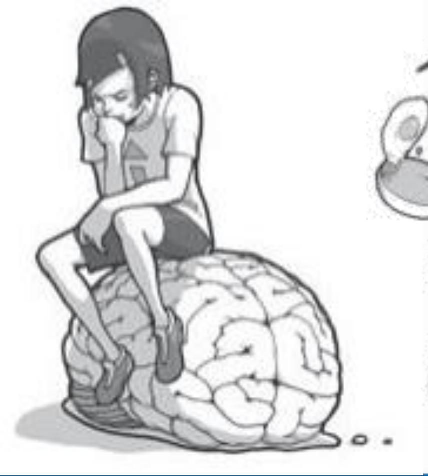
Embodied Intelligence & Morphological Computation

Classical approach

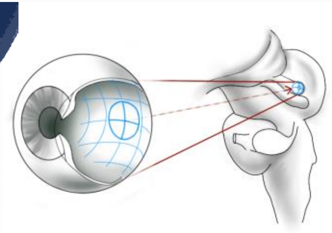
The focus is on the brain and central processing

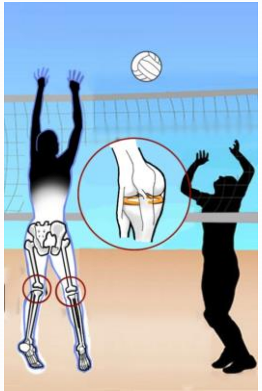
Modern approach

The focus is on interaction with the environment. Cognition is emergent from system-environment interaction



As any transformation of information can be named as *computing*, *Morphological Computation* endows all those behaviours where computing is mediated by the mechanical properties of the physical body





Arrangement
of the motor, perceptive and processing units

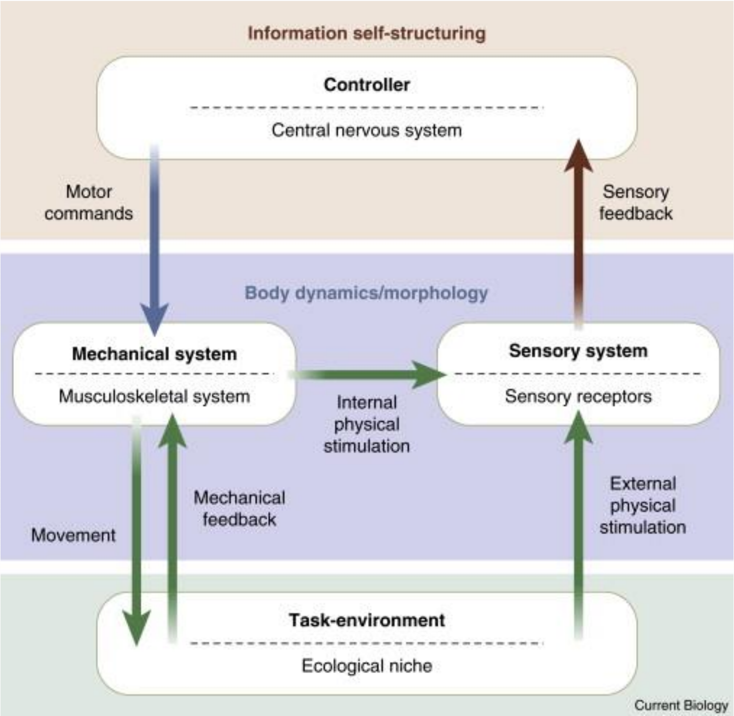
Shape
as body structure, specifies the behavioral response of the agent

Mechanical properties
allow emergent behaviors and adaptive interaction with the environment

Rolf Pfeifer and Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

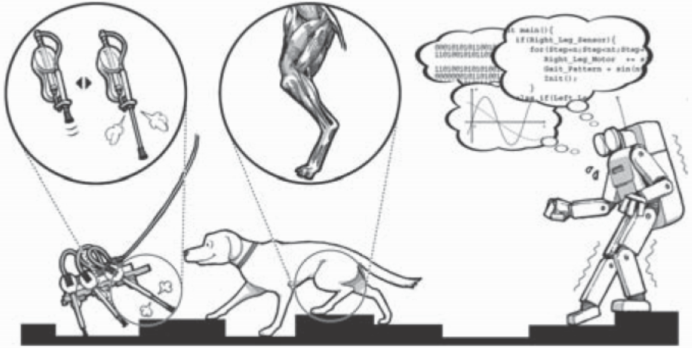
Zambrano D, Cianchetti M, Laschi C (2014) “The Morphological Computation Principles as a New Paradigm for Robotic Design” in *Opinions and Outlooks on Morphological Computation*, H. Hauser, R. M. Füchslin, R. Pfeifer (Ed.s), pp. 214-225.

Embodied Intelligence & Morphological Computation

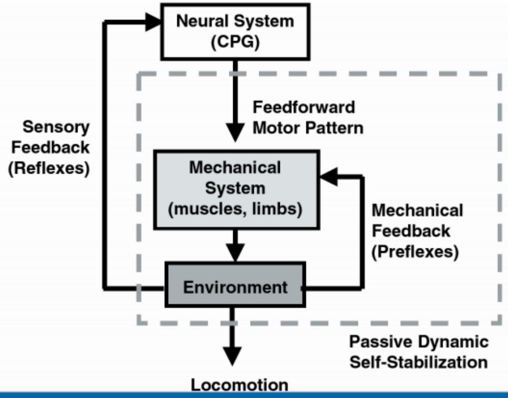


Adaptive behaviour emerges from the interaction between the morphology of the **body**, the **environment** and the **task.**

Many tasks become much easier if morphological computation is taken into account.



SPRAWL
Stanford Center for Design Research & UC Berkeley PolyPEDAL Lab



Open-loop/ feedforward control

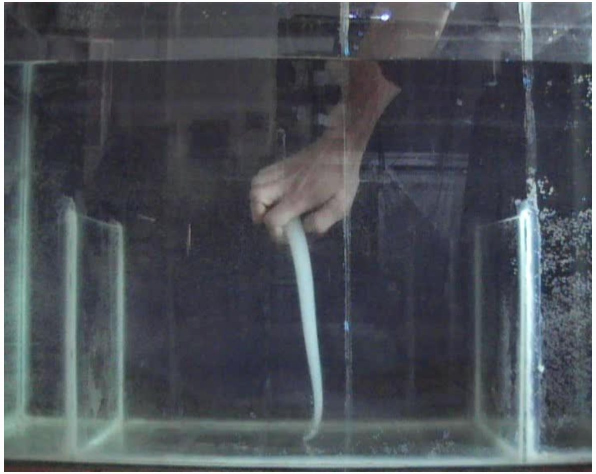
Passive viscoelastic structural elements

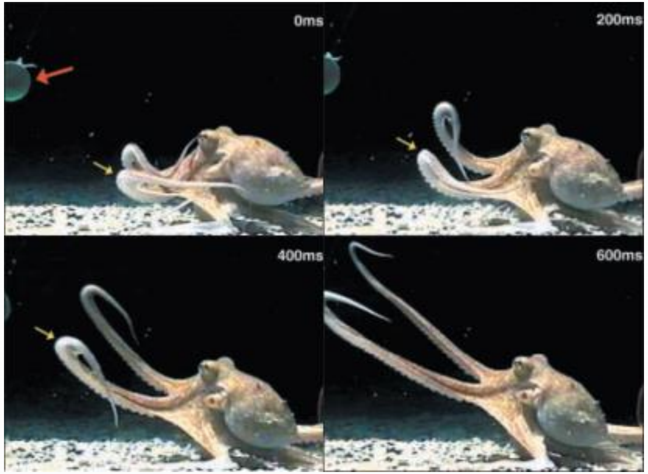
A new soft bodyware

Rolf Pfeifer and Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

JG Cham, SA Bailey, JE Clark, RJ Full and MR Cutkosky (2002). “Fast and Robust: Hexapedal Robots via Shape Deposition Manufacturing” *The International Journal of Robotics Research*, 21: 869

The octopus arm embodied intelligence



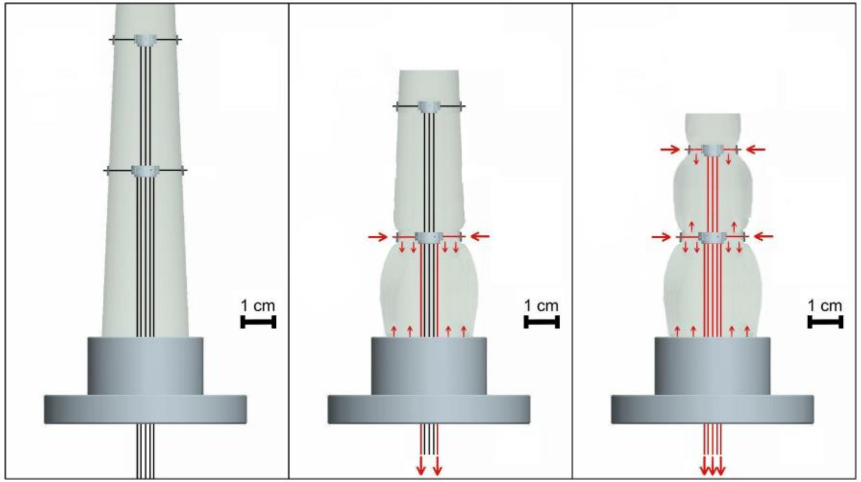


- stiffening wave from base to distal part, that can start from any part of the arm;
- movement executed in about 1 second, velocities in the range of 20–60 cm/s;
- control divided between central and peripheral: from brain: **3 parameters** (yaw and pitch of arm base and peak velocity of bend-point); locally: propagation of stiffness

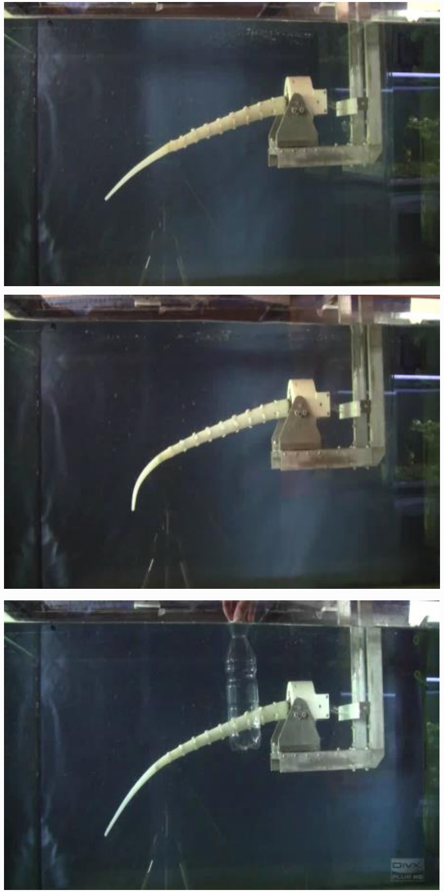
I. Zelman, M. Galun, A. Akselrod-Ballin, Y. Yekutieli, B. Hochner, and T. Flash (2009) Nearly automatic motion capture system for tracking octopus arm movements in 3D space, *Journal of Neuroscience Methods, Volume 182: 97-109*

L. Zullo, G. Sumbre, C. Agnisola, T. Flash, B. Hochner (2009) Nonsomatotopic Organization of the Higher Motor Centers in Octopus, *Current Biology, 19:1632-1636.*

Simplifying principles in reaching



- Silicone
- 9 sections of transverse and longitudinal cables (coupled)
- Simple activation pattern: sequential activation of sections, with equal activation of 4 longi-transverse cables per section

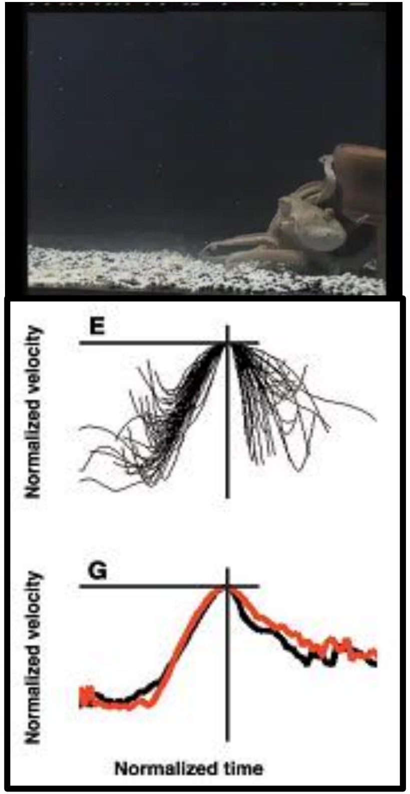


Cianchetti, M., Arienti, A., Follador, M., Mazzolai, B., Dario, P., Laschi, C. "Design concept and validation of a robotic arm inspired by the octopus", *Materials Science and Engineering C*, Vol.31, 2011, pp.1230-1239.

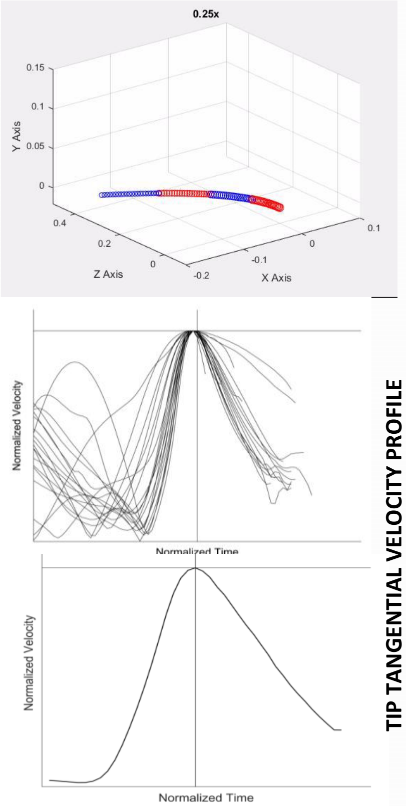
Simplifying principles in reaching

***morphological and environmental properties** are the factors that affects the invariant velocity profile observed*

Biological behaviour



Robot behaviour



TIP TANGENTIAL VELOCITY PROFILE

- Soft robot
- Passive distal part
- Water
- Neural controller (not octopus-like)

Environmental properties

Configuration	Learnable	Bend Propagation Strategy
Lower Environment Density (air)	No	N/A
Lower Environment Density (air) + Higher Body Stiffness and Viscosity	Yes	No
Actuators at Tip (4th Section)	No	N/A
Actuators at 3rd Section	Yes	No
Only two actuators at the base	Yes	Yes
Three Actuators at base + One at the tip	Yes	Yes
Shorter Manipulator (Only two sections)	Yes	No
Cylindrical Shape	No	N/A
Double module experiment	Yes	No

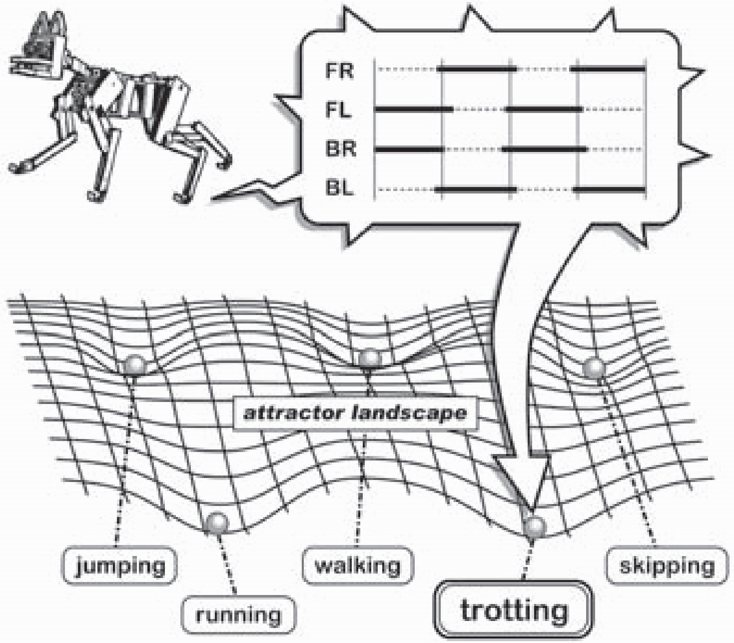
Morphological properties

Sumbre, G., Gutfreund, Y., Fiorito, G., Flash, T., & Hochner, B. (2001). "Control of octopus arm extension by a peripheral motor program", *Science*, *293*(5536), 1845-1848.

T. George Thuruthel, Falotico E., Renda F., Flash T., Laschi C., "Emergence of Behavior through Morphology: A Case study on an Octopus Inspired Manipulator", *Bioinspiration and Biomimetics*, under review.

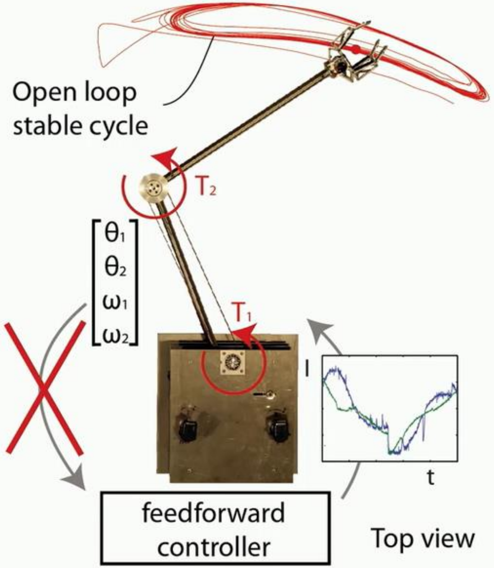
Self-Stabilizing Trajectories

Agents are dynamical systems and tend to settle into **attractor states**



It is possible to find open loop trajectories that are stable.

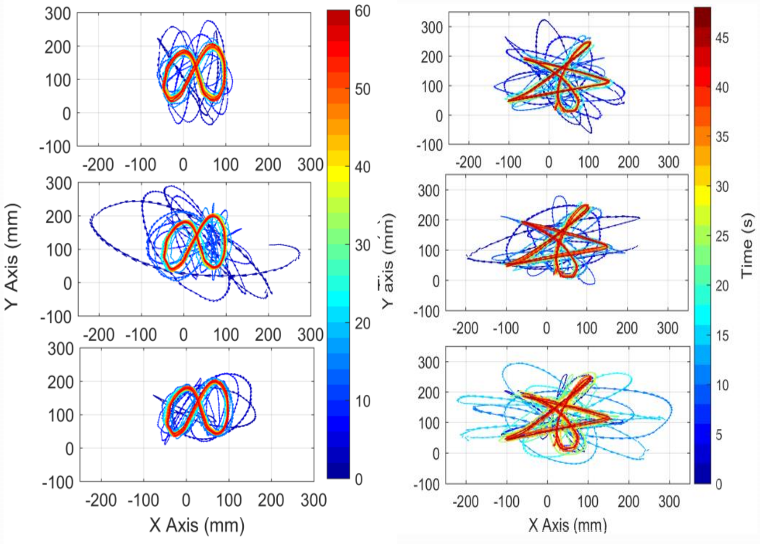
The trajectories depend on the robot dynamics and the control policy



Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Self-Stabilizing Trajectories

The unique dynamics of a soft manipulator exhibits larger number of dynamic attractors that can be used for stable open loop control



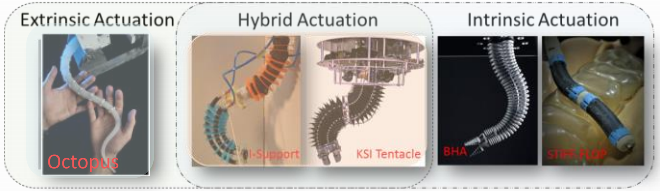
The stable trajectories can be observed using the learned forward model

Thuruthel T. G., Falotico E., Manti M., Laschi C. (2018). Stable Open Loop Control of Soft Robotic Manipulators. *IEEE Robotics and Automation Letters*, *3*(2), 1292-1298.

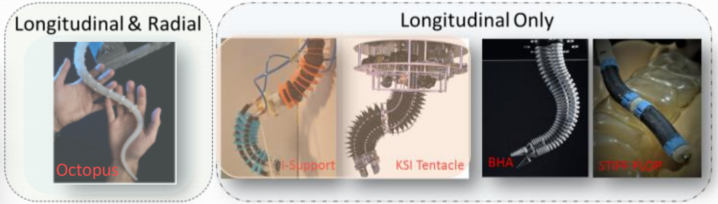
Approaches for control of soft robots

Soft Robots

Material



Arrangement



Functionality

Extrinsic: Tendons
- Contraction
- Bending

Hybrid Actuation: Tendons and Pneumatics
- Extension
- Contraction
- Bending

Dexterity

Variable Stiffness: antagonistic motion

Intrinsic: Pneumatics
- Extension
- Bending

Challenges

Environmental Effects/ Internal Fault

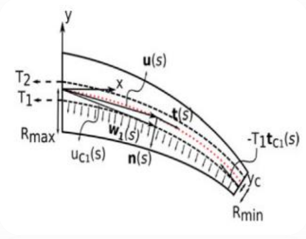
Redundant

Viscoelasticity

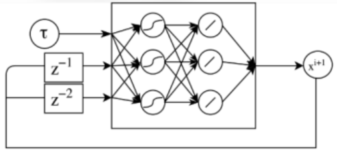
Platform Independence

Control Approach

Model-Based



Model-Free

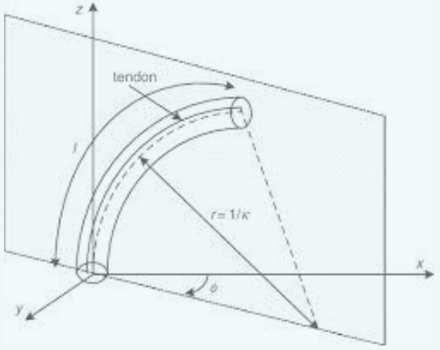


T. George Thuruthel, Y. Ansari, E. Falotico, C. Laschi (2018) “Control Strategies for soft robotic manipulators: a survey”, *Soft Robotics* 5(2)

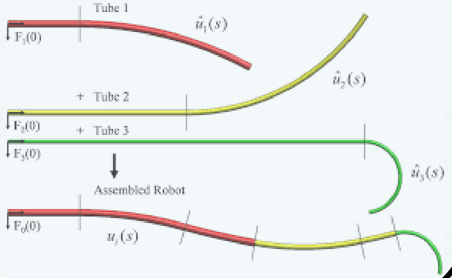
Model-based approach for control of soft robots

Continuous-functions

Constant Curvature Model

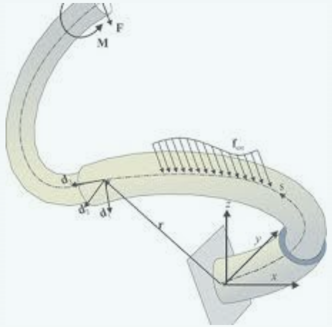


Piecewise Constant Curvature

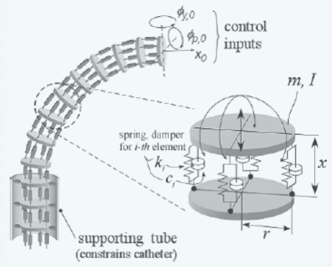


Discretized-functions

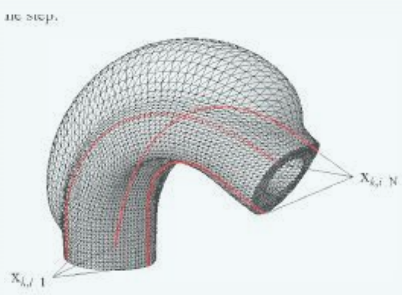
Cosserat-Rod Model



Lumped-Parameter Model



Finite Element Method

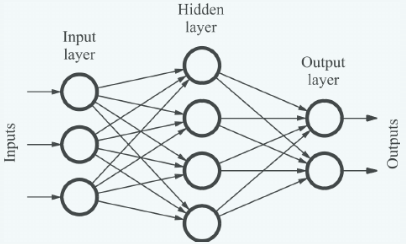


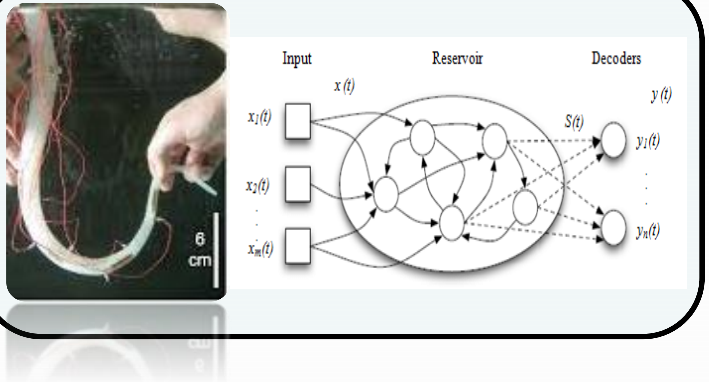
Increasing Computational Complexity and ‘Accuracy’

Model-free approach for control of soft robots

Supervised-learning

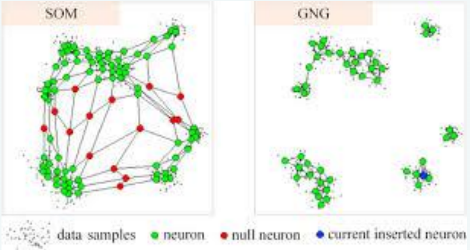
Feed-forward Neural Networks





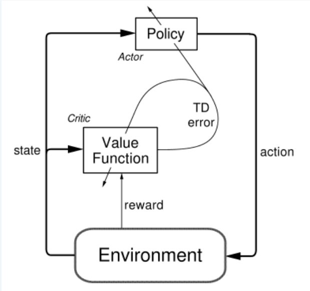
Unsupervised Learning

SOM and Growing Neural Gas

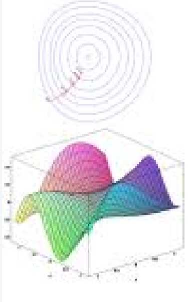


Reinforcement Learning

Actor-Critic



Policy-Gradient

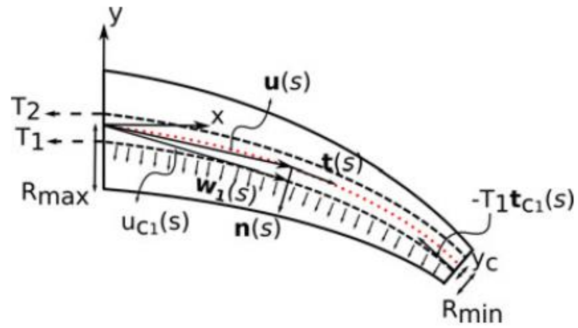


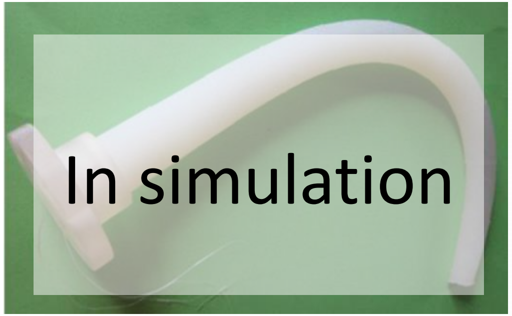
Comparison of a model-based and a model-free approaches

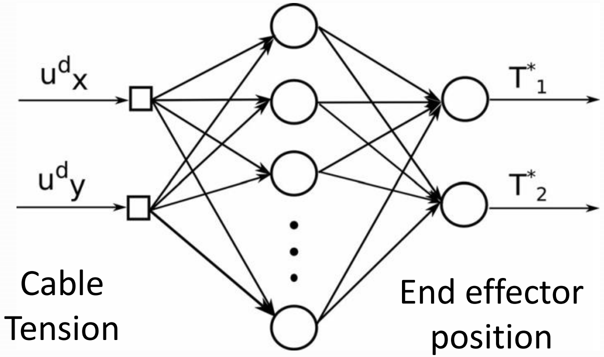
1. Jacobian-based Inverse Static Controller
2. Learning-based Control, by learning the inverse model.

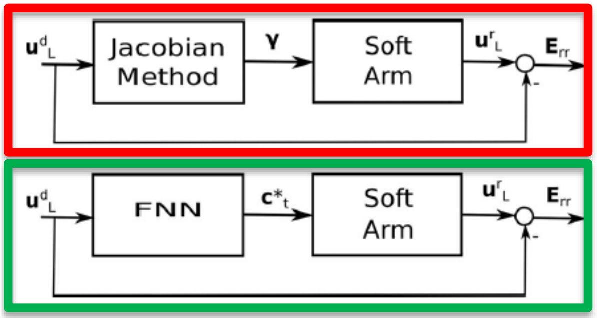
   Learning by collecting points and exploiting the approximation capability of a FNN, as for rigid robots

control the end effector position through the cable tension









Method (Cost)	Statistics Index	ERR/L [%]
JM (351ms)	Mean	0.27
	Std	0.03
	Max	0.32
NN (0.125ms)	Mean	0.73
	Std	0.55
	Max	3.1

Giorelli, M., Renda, F., Calisti, M., Arienti, A., Ferri, G., & Laschi, C. (2015). Neural network and Jacobian method for solving the inverse statics of a cable-driven soft arm with nonconstant curvature. *IEEE Transactions on Robotics*, *31*(4), 823-834.

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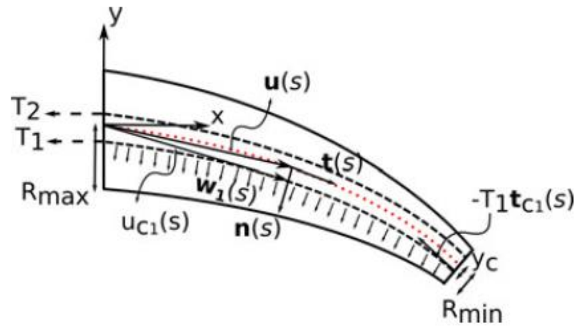
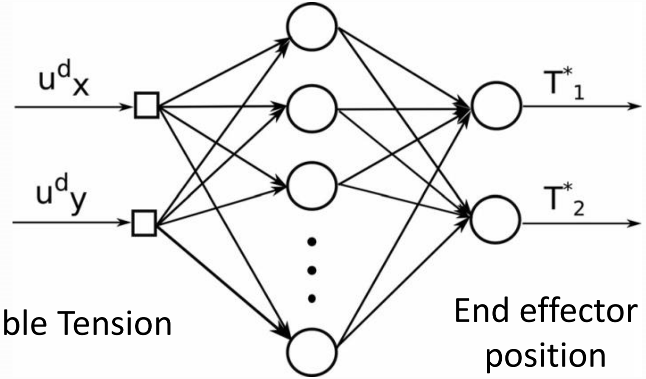
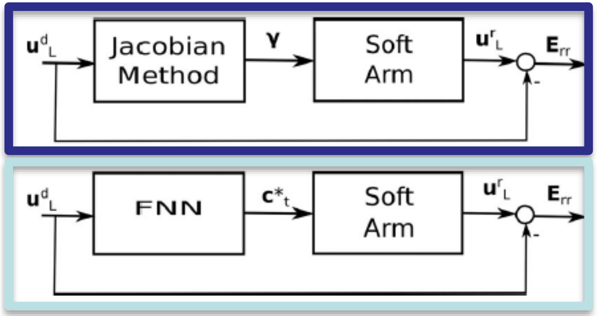




Cable Tension

End effector position



Method		Absolute (mm)	Percentage (%)
Jacobian method	*mean*	15.12	5.4
	std	8.10	2.89
	max	31.76	11.34
	$p_{\%}$		43.18
FNN	*mean*	7.35	2.62
	std	4.75	1.7
	max	22.22	7.94
	$p_{\%}$		91

Giorelli, M., Renda, F., Calisti, M., Arienti, A., Ferri, G., & Laschi, C. (2015). Neural network and Jacobian method for solving the inverse statics of a cable-driven soft arm with nonconstant curvature. *IEEE Transactions on Robotics*, *31*(4), 823-834.

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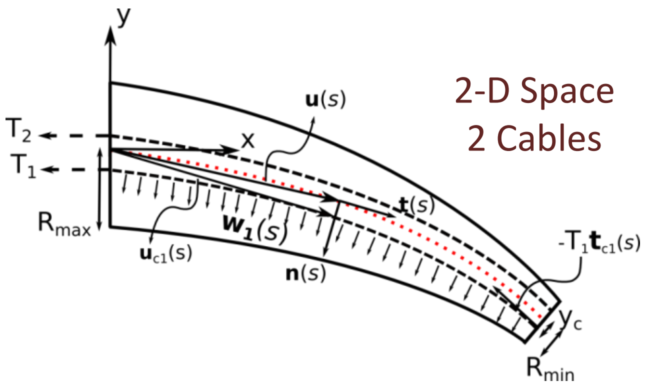
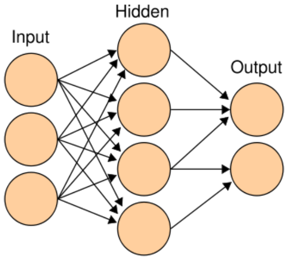


2-D Space
2 Cables

Tip Position



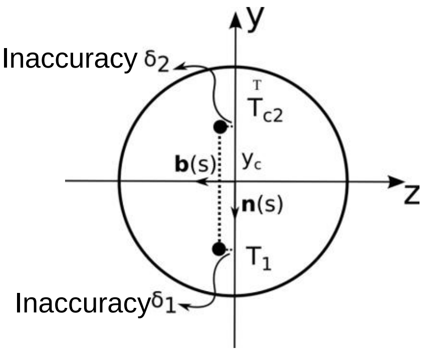
Cable Forces

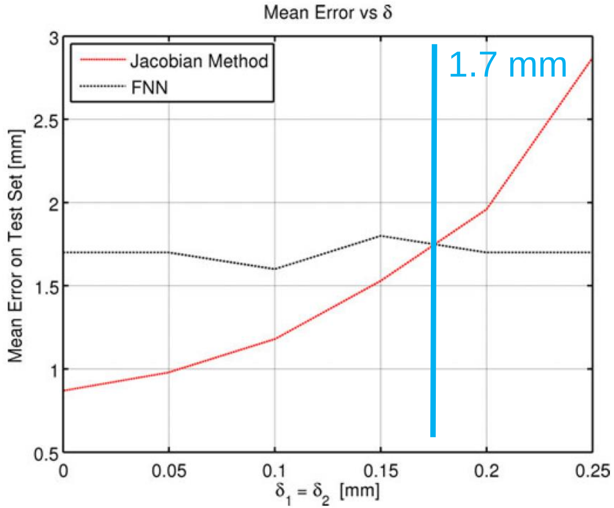
Increasing inaccuracy values

	Inaccuracies		Jacobian	FNN
Case	δ_1	δ_2	*mean*	*mean*
1	−0.25	0.25	1.02	1.5
2	0.25	0	1.26	1.8
3	0	0	0.87	1.7
4	0.05	0.05	0.98	1.7
5	0.1	0.1	1.18	1.6
6	0.15	0.15	1.53	1.8
7	0.2	0.2	1.96	1.7
8	0.25	0.25	2.87	1.7

All values are expressed in millimeters.

Simulated Defective Model





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Inverse Kinematic Controller

Kinematics: based on steady state assumptions

$\dot{x} = J(q)\dot{q} \quad \Rightarrow \quad \Delta x \approx J(q)\Delta q$

Learning a **Differential Inverse Kinematics** formulation : $\dot{\boldsymbol{x}} = J(\boldsymbol{q^o})\ \dot{\boldsymbol{q}}$

This allows for redundancy resolution, robustness to modelling errors

The learned mapping is : $(\boldsymbol{x}_{i+1}, \boldsymbol{q}_i, \boldsymbol{x}_i) \rightarrow (\boldsymbol{q}_{i+1})$

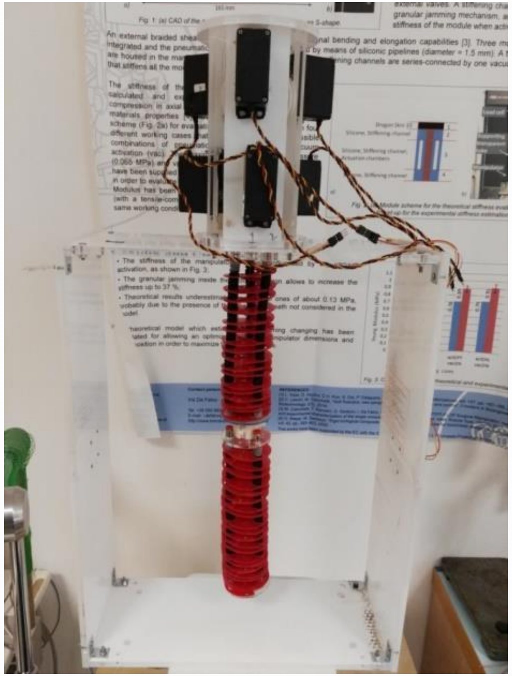
LEARNING

- 2000 sample points divided in the ratio 70:30 for training and testing respectively
- 2 hours for data collection, training, set-up

TESTS

25 random points selected from workspace

	Mean Error	Standard Deviation
Position (mm)	5.58	3.08
X- axis rotation (degrees)	2.76	5.42
Y- axis rotation (degrees)	1.84	1.83
Z- axis rotation (degrees)	3.85	7.02



I-Support Prototype

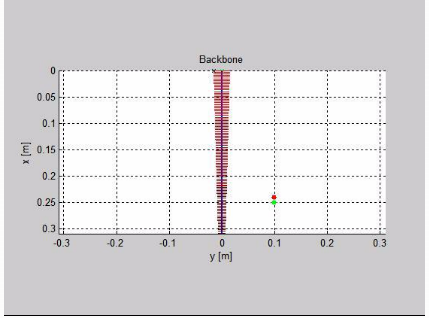
Six DoF Hybrid System (Pneumatic and Tendon)

George Thuruthel T, Falotico E., et al. "Learning closed loop kinematic controllers for continuum manipulators in unstructured environments." *Soft robotics* 4.3 (2017): 285-296.

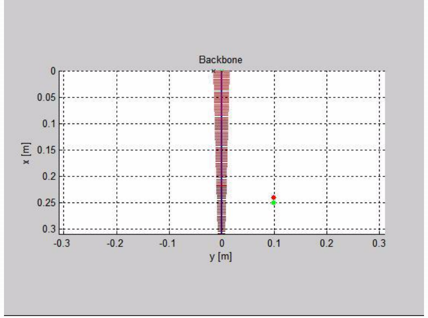
Inverse Kinematic Controller – results in simulation

Only Position Control

Green Point is the target position

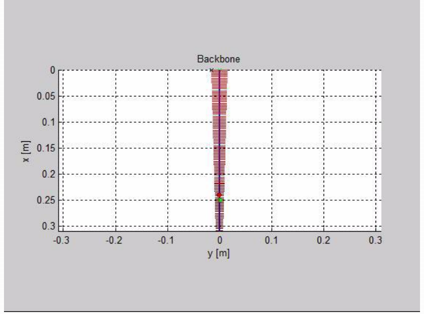


Position and Orientation Control



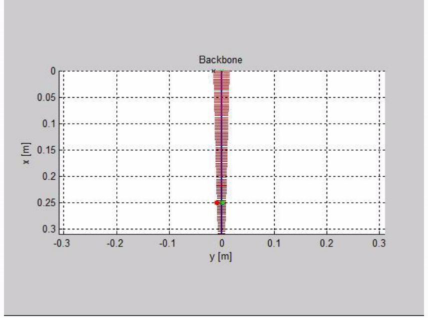
Target Orientation: the vector from the red point to the green point , i,.e parallel to X axis

Behavior at unreachable ‘points’



In this case, some of the target orientations are impossible to reach, however we can still see stable behavior of the solver

Varying Orientation

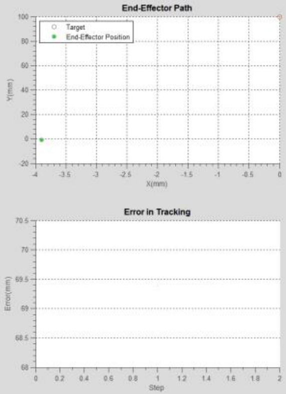


180° rotation of the manipulator without changing the position

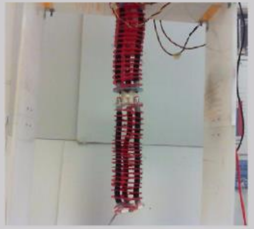
T. G. Thuruthel, E. Falotico, M.Cianchetti, F. Renda, C. Laschi, (2016). “ Learning Global Inverse Statics Solution for a Redundant Soft Robot”, *In Proceedings of the13th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2016)*, pp 303-310

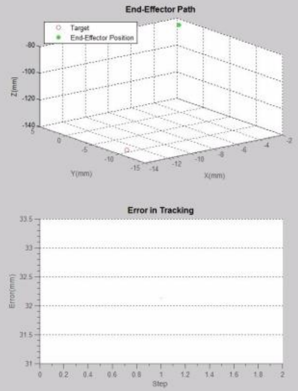
Inverse Kinematic Controller – results on the robot

Line Following

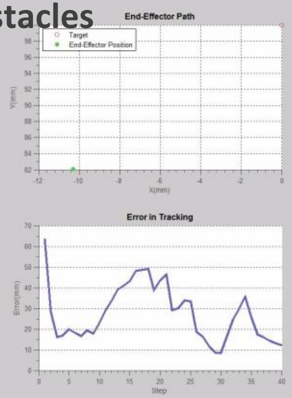


Disturbance Rejection

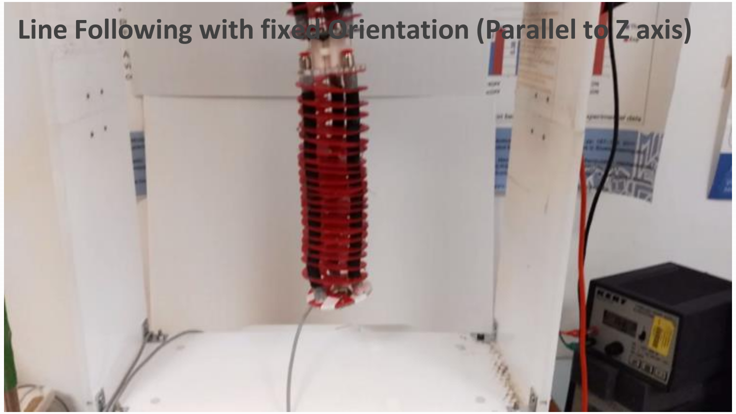


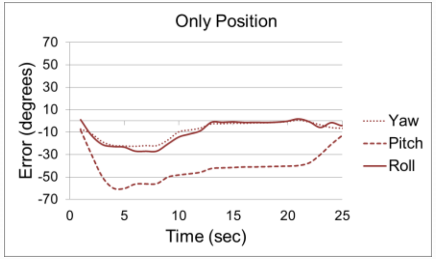


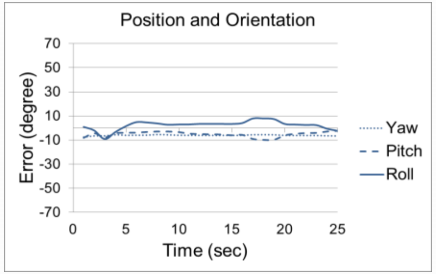
Line Following with obstacles



Line Following with fixed Orientation (Parallel to Z axis)



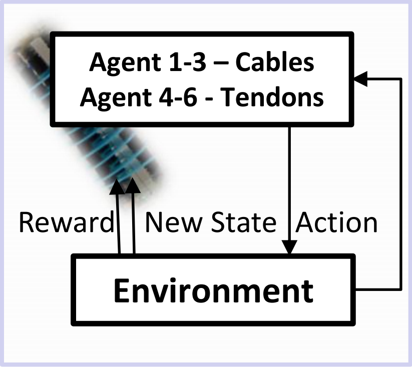




George Thuruthel T, Falotico E., et al. "Learning closed loop kinematic controllers for continuum manipulators in unstructured environments." *Soft robotics* 4.3 (2017): 285-296.

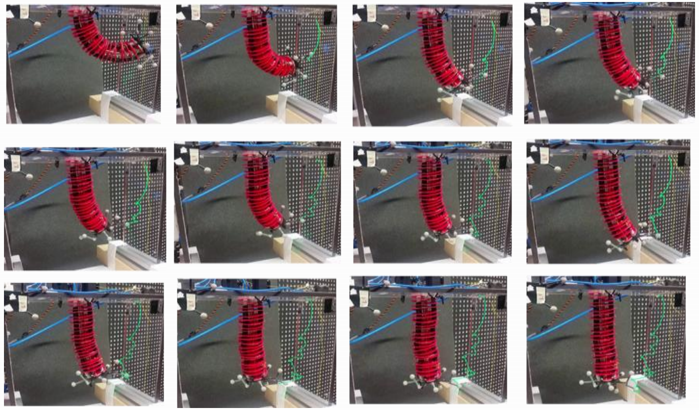
Inverse Kinematic Controller and stiffness optimization

Multiagent Systems + Hierarchical Reinforcement Learning

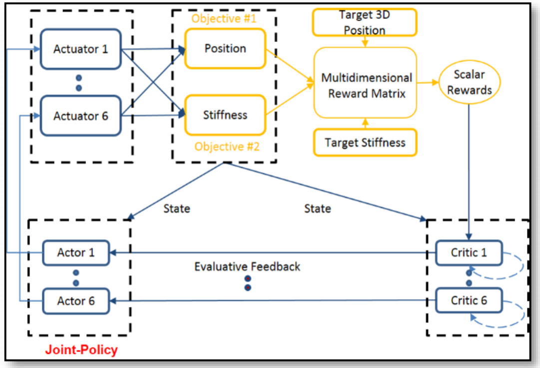


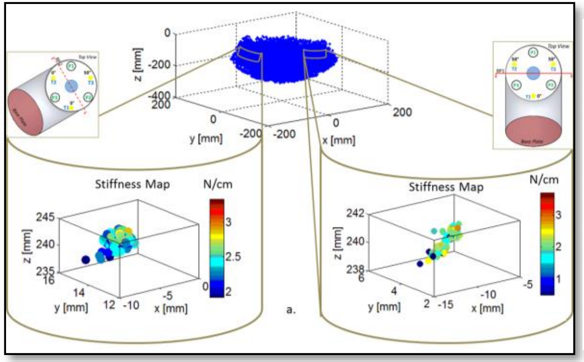
- ❖ Feedback-based controller
- ❖ Learning Principle –
  - ❖ Linear approximation
  - ❖ Distributed Actor-Critic
  - ❖ SMDP runs for a single-trial
  - ❖ Action-set chosen dynamically

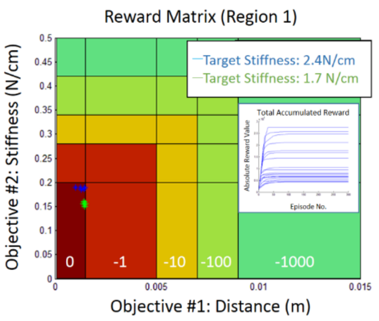
Tracking accuracy < 9mm but policy is discontinuous

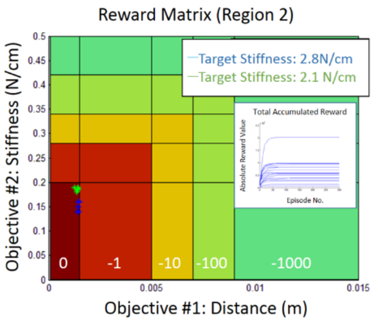


Multiagent Systems + Hierarchical Reinforcement Learning + Multiple Objectives









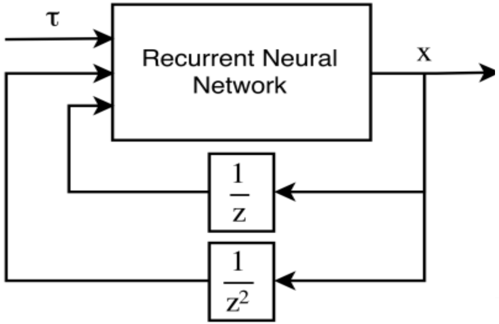
Ansari, Y., Manti, M., Falotico, E., Cianchetti, M. and Laschi, C., 2018. Multiobjective optimization for stiffness and position control in a soft robot arm module. *IEEE Robotics and Automation Letters*, 3(1), pp.108-115.

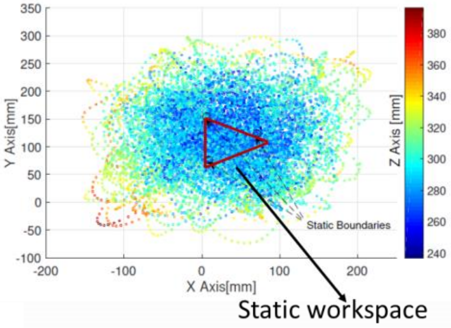
Dynamic Controllers – open loop

Controlling the soft manipulator both in space and time

$$(\tau, x, \dot{x}) \rightarrow \ddot{x}$$

$$\left(\tau, x^{i}, x^{i-1}\right) \rightarrow\ x^{i+1}$$





Sampling

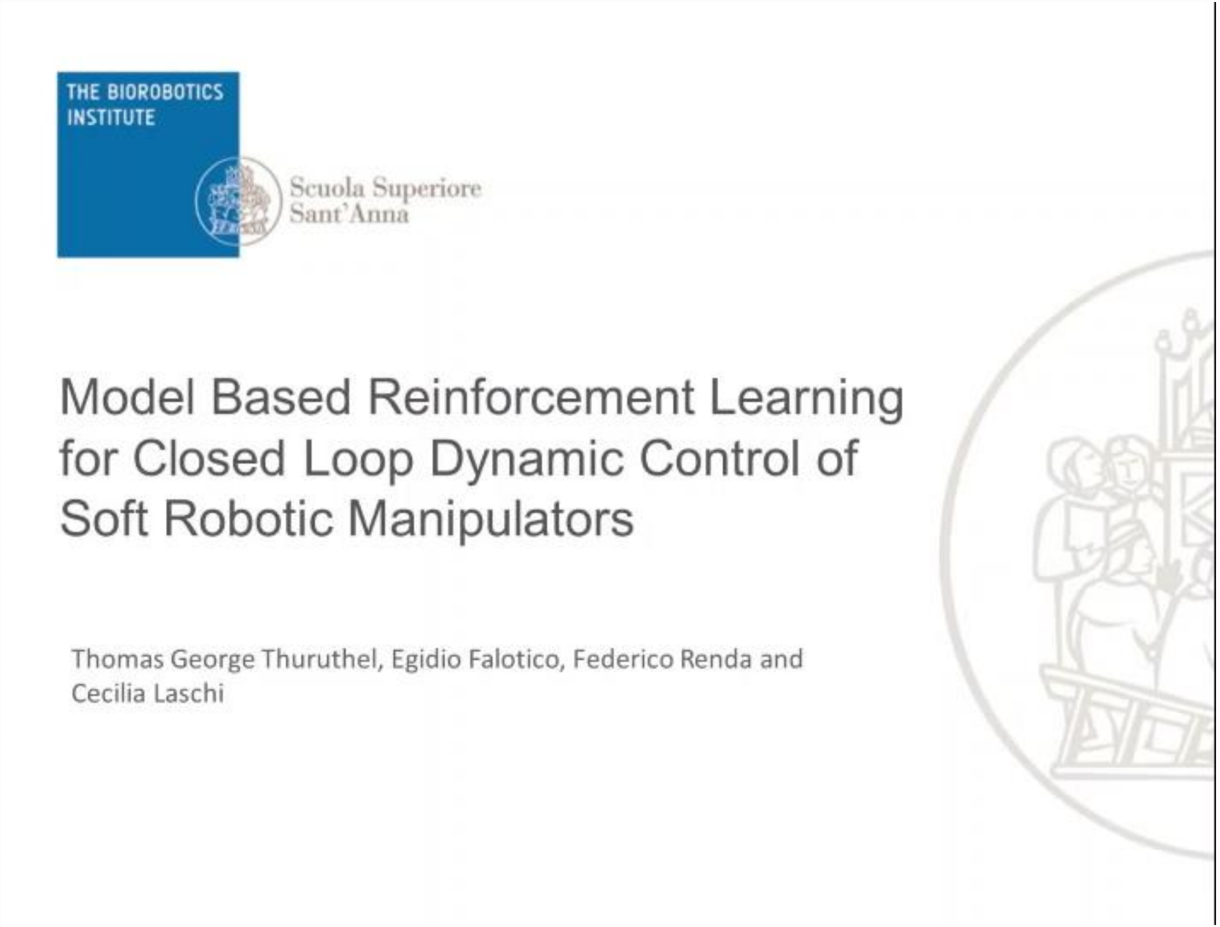
Slow circle task

Fast circle task

Thuruthel, T. G., Manti, M., Falotico, E., Laschi, C. 2018. "Stable Open Loop Control of Soft Robotic Manipulators." *IEEE Robotics and Automation Letters* 3(2):1292-1298.

Dynamic Controllers – Closed-loop control

Closed loop control policies can be generated using **model-based reinforcement learning**



Use case for soft robots: assisting elderly citizes in daily activities

State-of-art

Automated shower seats safely mobilize a user in the showering environment. This reduces the risk of falling which is the primary source of injury in elderly citizens

The unaddressed challenge

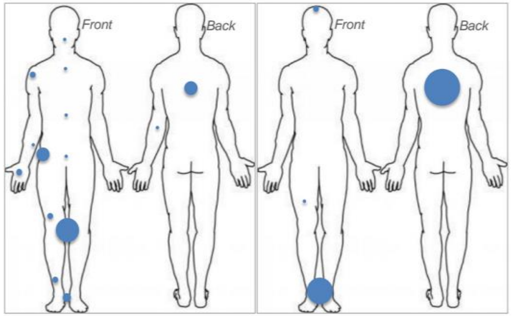


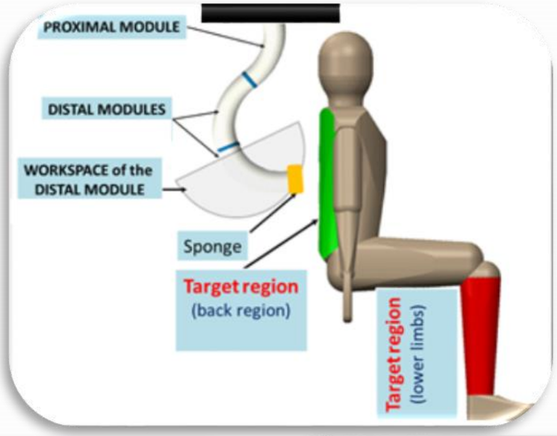
Figure 3-7. Overview of pain sensitive body parts on the left and non-reachable body regions on the right. The size of circles is based on the frequency of primary users' indications (N=30).

Elderly citizens rely on professional healthcare to assist in the main bathing activities which is a loss in **integrity and independence.**

Use case for soft robots: assisting elderly citizes in daily activities

I-Support: A service robotics system for bathing tasks

Proposed Solution



Central Design Concept

Proximal Module
to compensate gravitational effects produce by latter modules in series

Distal Module(s)
to reach target regions
to perform bathing task

Technical Requirements for Design

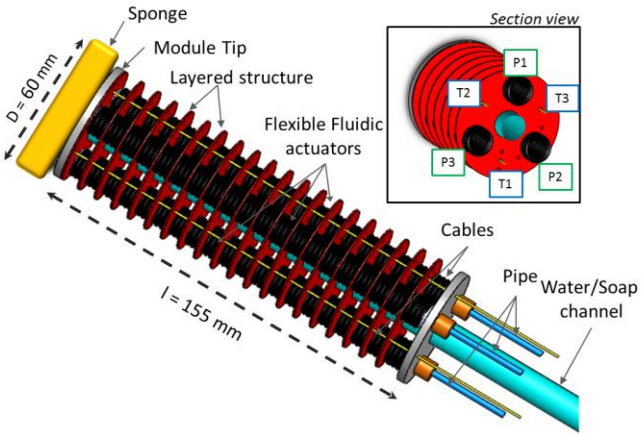
- Safe human-robot interaction
- High dexterity
- Variable Stiffness
- compliant while moving around the user stiff during scrubbing tasks

Technical Requirements for Control

- Simultaneous optimization of position and stiffness

Use case for soft robots: assisting elderly citizes in daily activities

I-Support: A service robotics system for bathing tasks

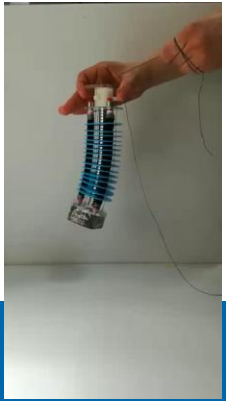


COMPONENTS

1. Cables (3)
2. Flexible Fluidic Actuators (3)
3. Sponge
4. Layered structure
5. Water/soap inner tube

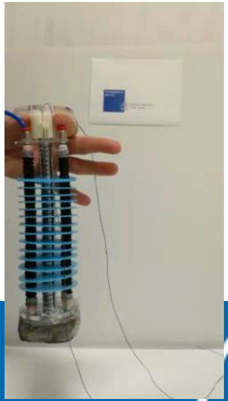
FUNCTIONALITIES

1. Bending on multiple planes



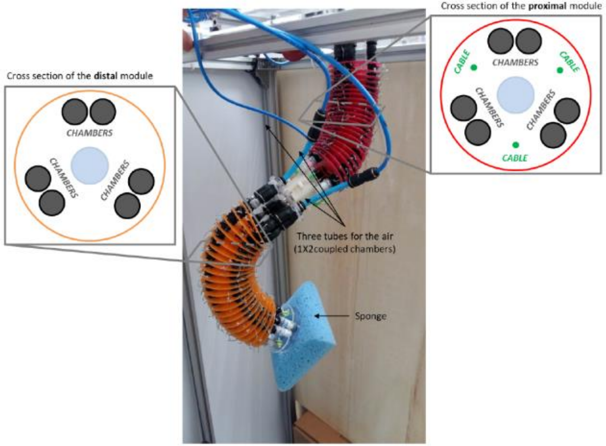
2. Contraction

3. Stiffness Modulation



Use case for soft robots: assisting elderly citizes in daily activities

The I-support Arm



- Combination of two different actuation technologies:

- **Mc-Kibben based flexible fluidic actuators**, that enable elongation and omni-directional bending with low accuracy

- **Tendon-driven mechanisms**, that can implement shortening and (redundant) omni-directional bending with high movement resolution, and high accuracy.

Summary

- Embodied intelligence provides symplifying principles for robot behaviour
- Robot behaviour is simpler to control, but design becomes more complex
- Model-free, learning-based approaches are better suited in soft robotics, not only because soft robot models are more difficult and less accurate, but especially because they better capture body contribution to control
- Soft robots achieve further abilities in real world, for more robot applications