Control in Technological Systems and Physical Intelligence: an emerging theory

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Bradly Alicea

bradly.alicea@ieee.org

http://www.msu.edu/~aliceabr/

Abstract

The transduction and processing of physical information is becoming important in a range of research fields, from the design of materials and virtual environments to the dynamics of cellular microenvironments. Previous approaches such as morphological computation/soft robotics, neuromechanics, and embodiment have provided valuable insight. This work approaches haptic, proprioception, and artificial physical sensing as all part of the same subject. In this presentation, three design criteria for applying physical intelligence to engineering applications will be presented.

These criteria have several properties in common, which inspires two types of end-effector model: stochastic (based on a spring) and deterministic (based on a piezomechanical array). The generalized behavior and output dynamics of these models can be described as three findings summarized from previous work. In conclusion, future directions for modeling neural control using a neuromorphic approach will be discussed.

Introduction

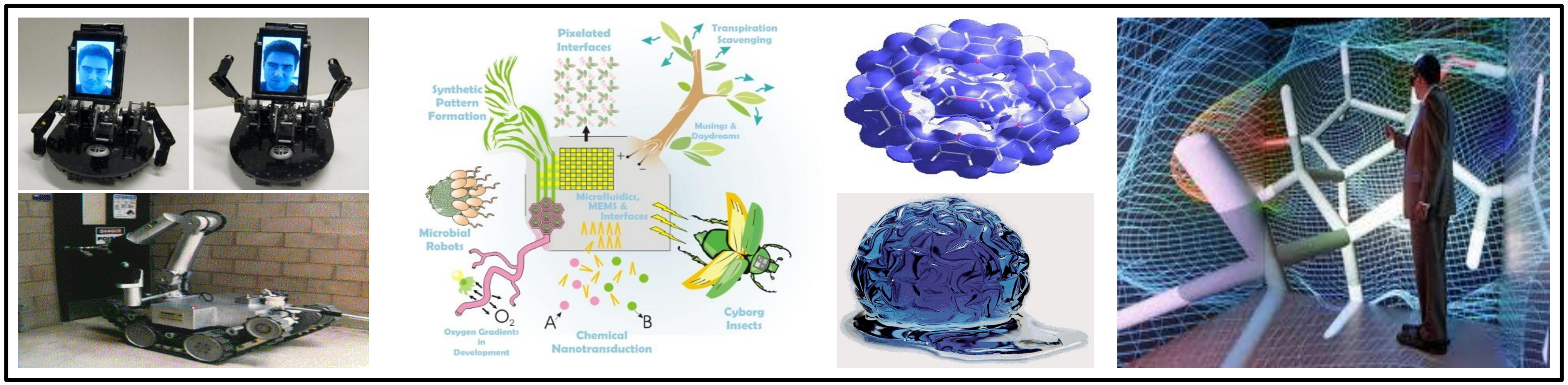
An increasing number of technological applications, from controlling virtual worlds to creating artificial organs, require intelligent physical control that meets several criteria

Research that combines materials, “physical” perception, and intelligent control may provide a useful tool for an emerging frontier of engineering and medicine

Nano	Scale-appropriate applications	**Micro**	Scale-appropriate applications	**Humans**	Scale-appropriate applications	**Landscapes**	Scale-appropriate applications

Telerobotics

Smart Materials



Cellular Microenvironments

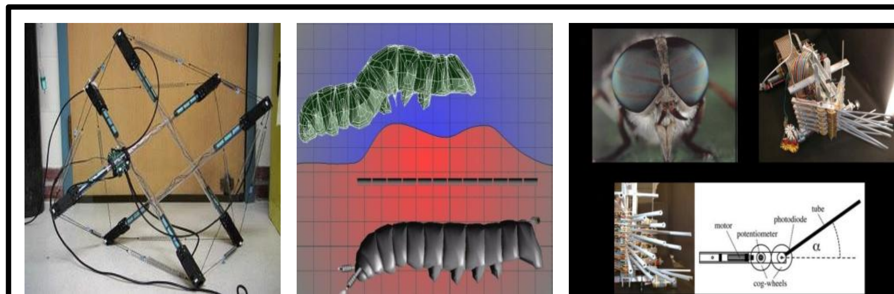
Immersive Virtual Worlds

Alternate Approaches/Inspiration

Morphological Computation/Soft Robotics

* computation, information processing done at periphery of nervous system

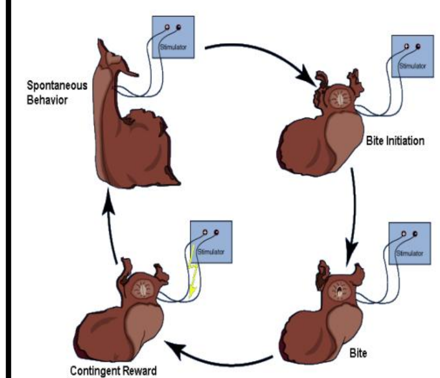
* scaling of muscle power, limbs, effectors to neural control networks



Neuromechanics

* what is the relationship between neural circuits and movement-related parts of the body?

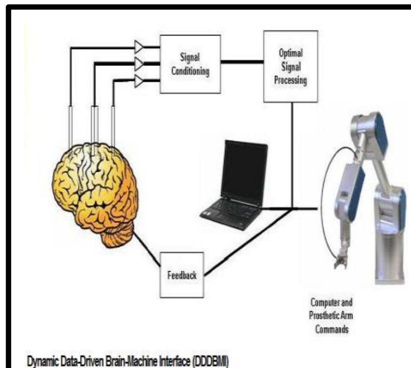
* mechanical parameters (surface reaction forces, gravity, hydrodynamic drag) essential to movement behavior



Embodiment

* the entire body (along with the brain) is essential for action (movement-related behaviors)

* coupling between neural circuits and morphological effectors essential



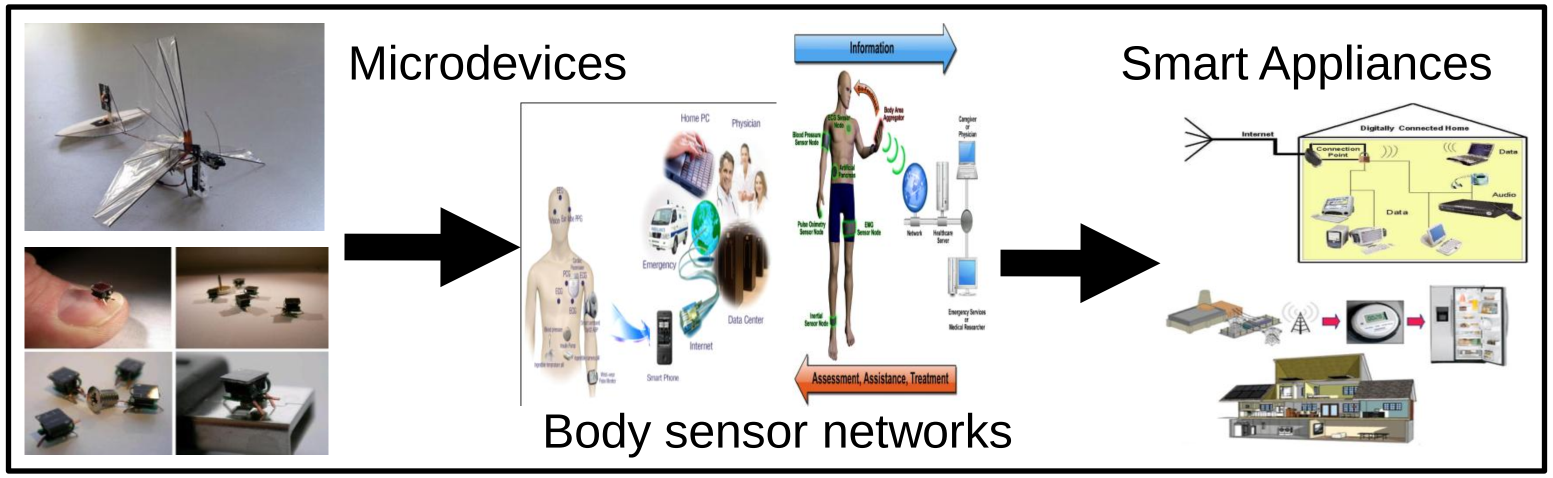
Criterion #1

Must be closely integrated with or mimic physiological functions (movement, neuromuscular function, touch)

Reinterpret existing literature in these areas as “physical” intelligence

Physical control performs not only functions such as prediction and pattern recognition, but also adaptation to extreme/repeated stimuli and self-repair

Control problem: How do we embody physical objects, systems with autonomous intelligence?



* objects at different scales (e.g. microdevices, body sensor networks, appliances)

* how do we compute physical inputs? Analogous to a nervous and/or biological system?

* beyond neural networks or other approaches to integrating physiological systems with a self-adapting autonomous intelligence

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Criterion #2

A strategy for understanding the structure of surfaces both commonly and uncommonly encountered.

Surface properties include both the texture of objects and reaction forces from objects and the environment in general.

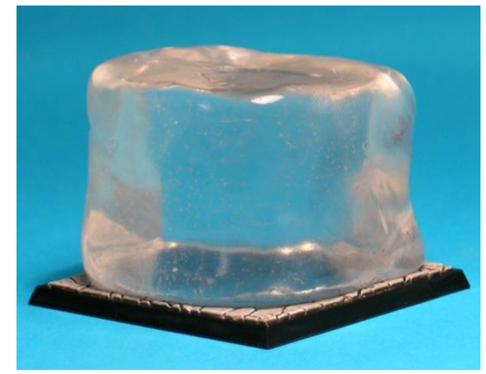
Surface and effector properties:

* physical intelligence operates on and is shaped by surface properties

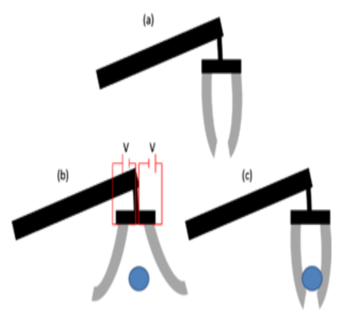
Morphology alone: morphology used to locomote over, explore surface – no way to retain information

Nervous System alone: nervous system can sense surface properties - no way to transduce signal

Morphology + Nervous System: transduce, retain information, and predict response



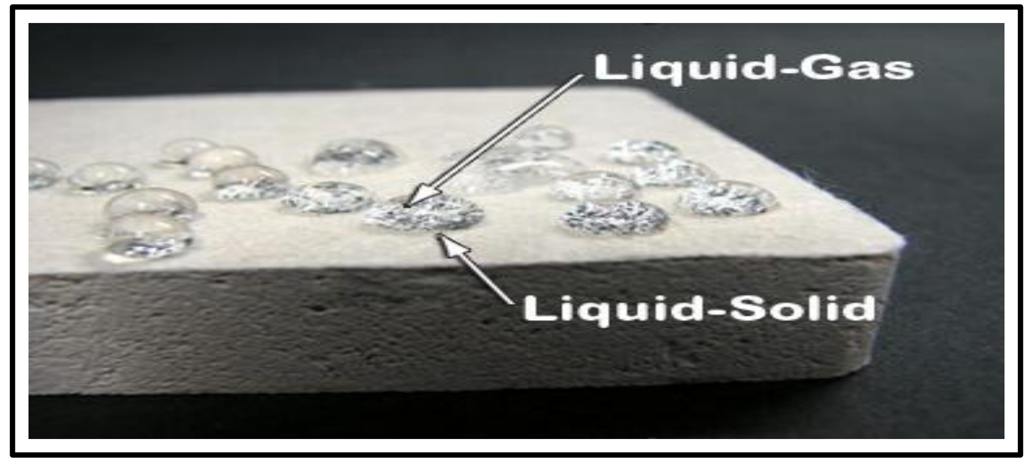
Uncommon surfaces: non-Newtonian fluid (left), gelatinous (right)



Effector composition: electroactive gripper (left); compliant polymers such as flexicomb (middle), Nokia's morph cellphone (right)

Criterion #3

Exception-handling “spiky” or “bursty” environmental inputs.

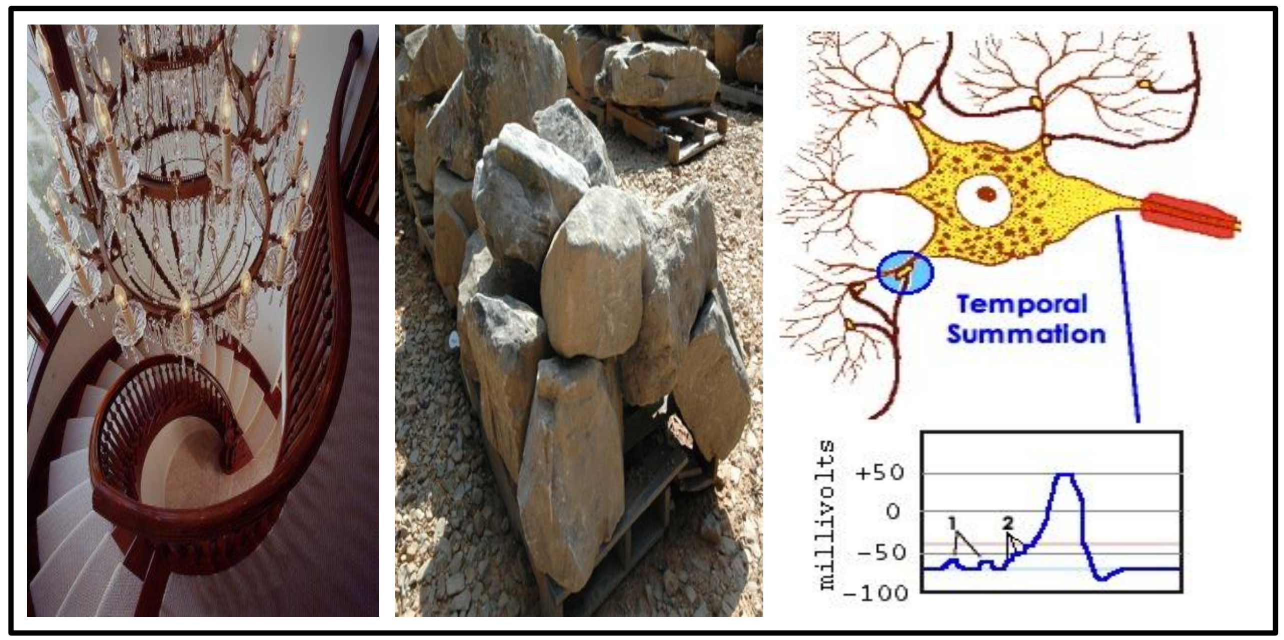


* boundaries between material phases (e.g. liquid, solid)

* rare events, temporal fluctuations

To truly understand the nature of intelligent control requires us to consider non Gaussian-noise present in environmental stimuli. Why is this important?

* surfaces are uneven, proprioception requires temporal summation



Necessary components:
* neural coding at level of controller

* set-theoretic model of environment (sensory-reachable volume approach)

How do these criteria have in common?

How are the reactive properties of materials and physical sensory systems characterized by intelligent control?

* materials have global parameters (stiffness, deformability)

* interaction with surfaces (static, dynamic properties) produces inertial, resistive by-products (nervous system must “match” environment)

* morphology (end-effector) can be scaled (length-wise, overall geometry) to either minimize or take advantage of these environmental properties

* each end-effector covers a finite space (reachable sensory volume) that determines the representational “world”. Reach of all effectors at all time points = “universe”

* learning is based on variability of environment and partitioning/connectivity between neuronal units (structural modular intelligence)

Mechanical Model - Deterministic

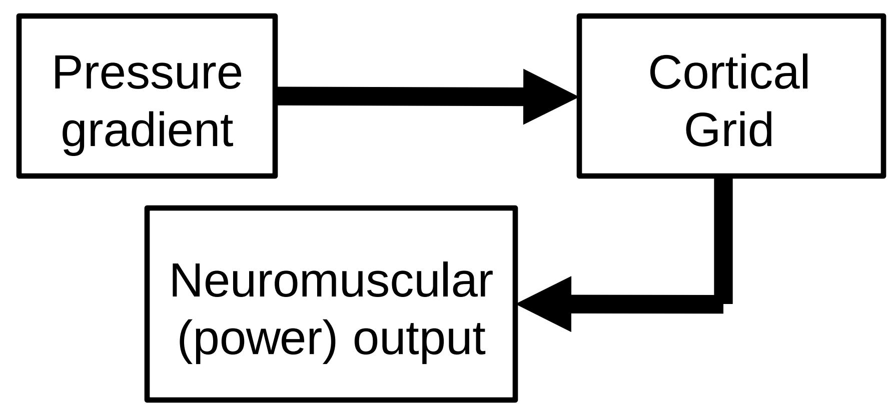
Piezomechanical (pressure-sensitive capacitor):

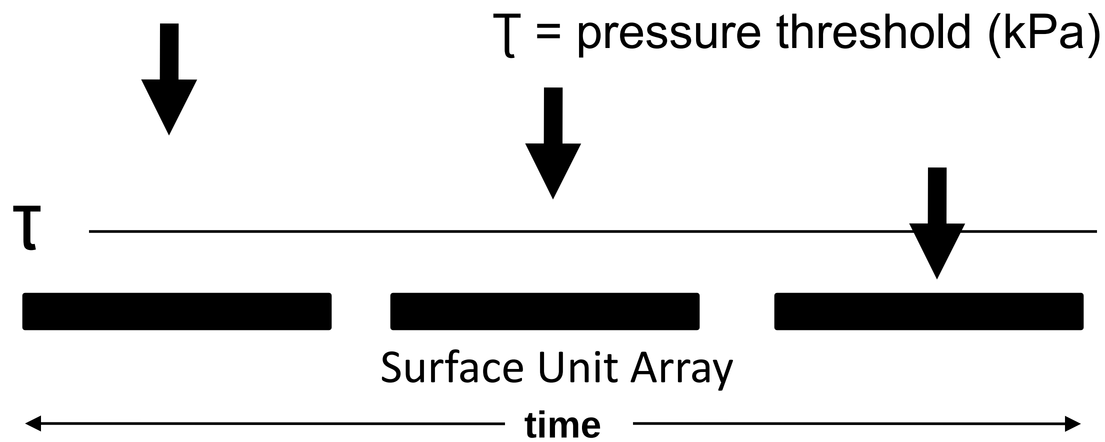
Deterministic model:
Spring model provides a graded or binary response (reaction force to threshold)

On/off response: piezomechanical (e.g. mechanorheological fluids, mechanoactive polymers)

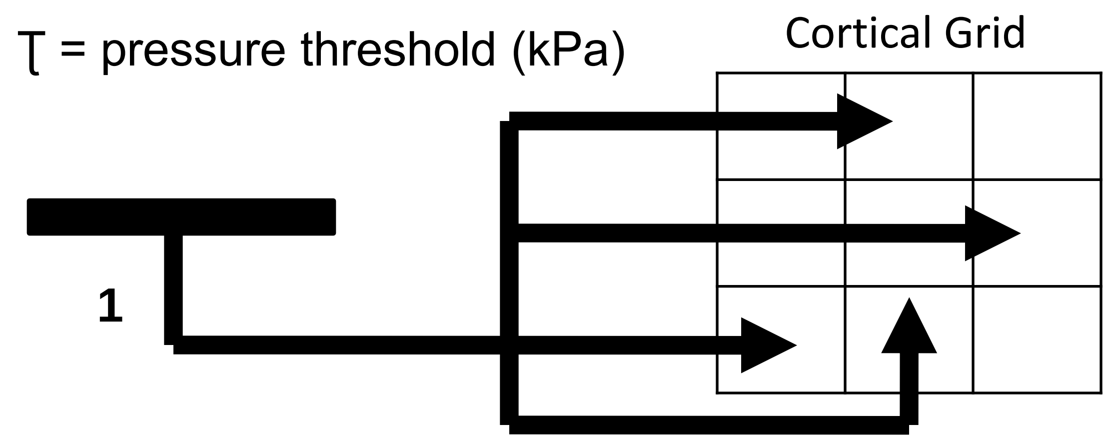
Pressure-sensitive media acts as a logic gate

Pressure inputs to modular nervous system





Depress surface until pressure threshold is reached

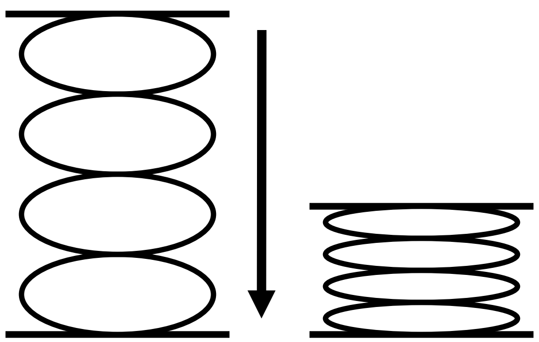


When pressure exerted on surface unit , signal generated (binary output , 1 = above threshold)

Mechanical Model - Stochastic

Muscle (dampened spring):

Stochastic model:
spring acts as a logic gate (fuzzy response)



K = spring constant

Contraction occurs at spring constant K, output is graded

How can noise and uncertainty be used to our advantage?

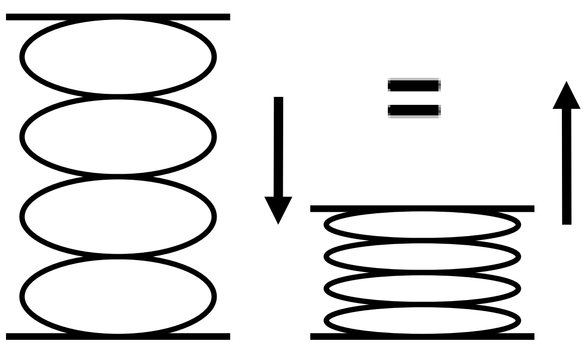
Selective lack of control during behavior (“suspended slinky” condition)

↓

Introduction of a robustness mechanism (prepare for rare events)

Does this lead to anticipatory response? Compare with findings related to environmental state

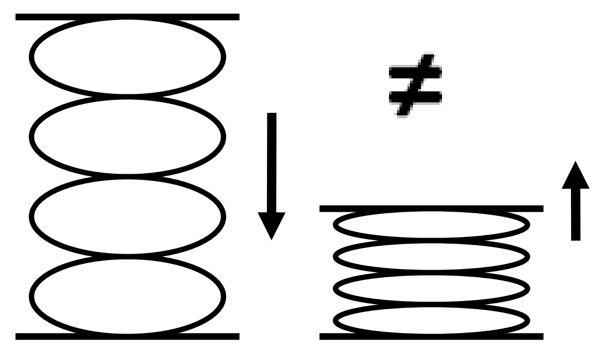
Power-dependent:



Sensed input proportional to produced output

Tight linkage between environment, morphology, neural control

Power-independent:



Sensed input not proportional to produced output

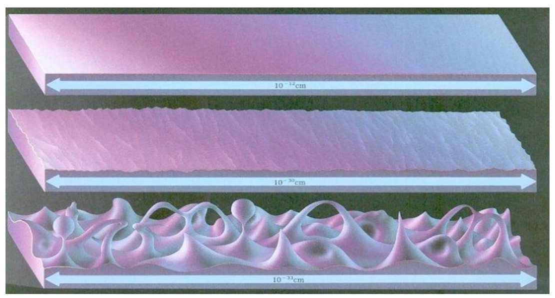
Relaxed linkage between environment, morphology, neural control

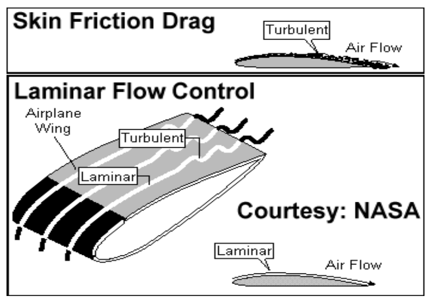
Finding #1

The “physical response” is an ability to match the amount of power produced with the amount and/or regularity of forces sensed in the environment.

Matching response between forces sensed and forces produced by nervous system in response

“Matching” allows for a mimicry of sensorimotor integration in artificial and hybrid intelligent systems

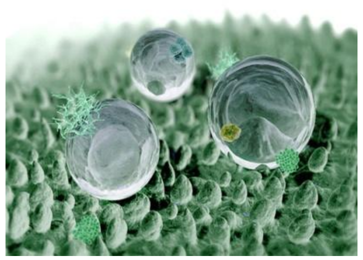


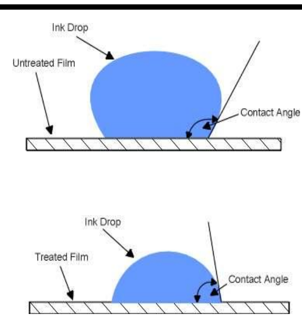


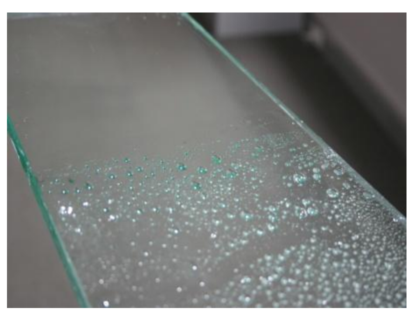
When mismatch occurs (due to perturbation), performance suffers but opens door for adaptation

Scaling of effector length with magnitude of environmental forces encountered

Prediction of local/global physics at many different spatial scales and magnitudes







Environmental switches (temporal) required to induce adaptation (form of supervised learning)

Finding #2

Switching between surfaces with different properties can create a exception-handling mechanism related to learning

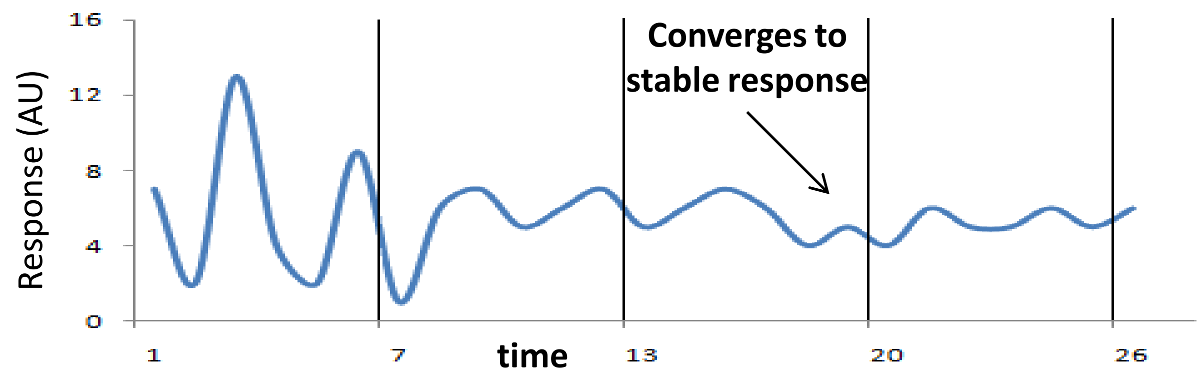
Switching dynamics observed in systems ranging from attentional control to bacterial physiology

Switching between environments allows for the development of an anticipatory response (adaptation – learning related)

Experimental setup: hard-soft-hard-soft

Constant switching forces a generalized response (environment exhibits maximum entropy)

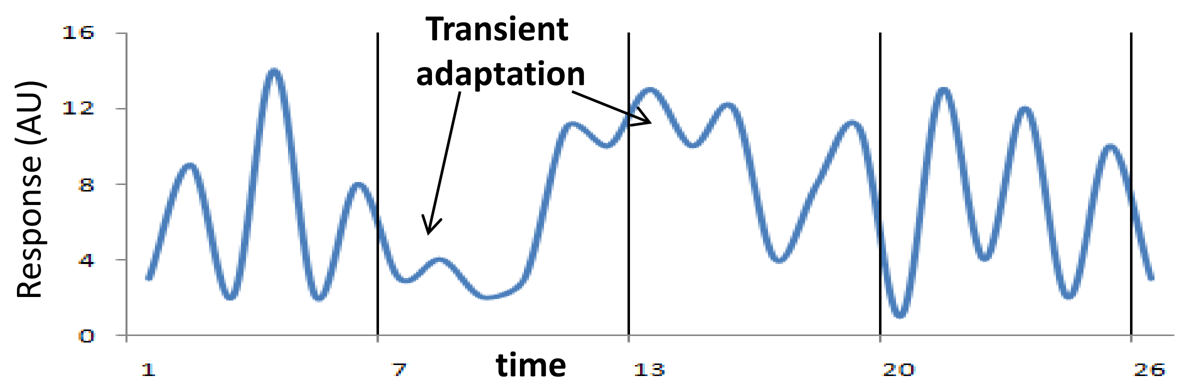
Anticipatory response (generalized pseudo-data)



Experimental setup: hard-hard-hard-soft

Unexpected switching forces variation with local adaptation (response exhibits maximum itinerance)

Non-anticipatory response (generalized pseudo-data)



Finding #3

Coupling motion with surface reaction forces provides a mechanism for learning.

Experimentally realized using virtual worlds and robotic models

Variable motion + reaction forces = mechanism for exploration and learning in touch, proprioceptive systems

Proprioception (pendular model)

Touch (discrete dynamical model)

Pendular model: use a pendulum with a chamber at effector

* chamber filled with material in a particular phase (e.g. liquid, gas, solid)

  * when swung, inertial/coriolis forces generated.

  * different materials/phases = different dynamics.

  * dynamics of environment also vary by radius of gyration, amplitude of swing.

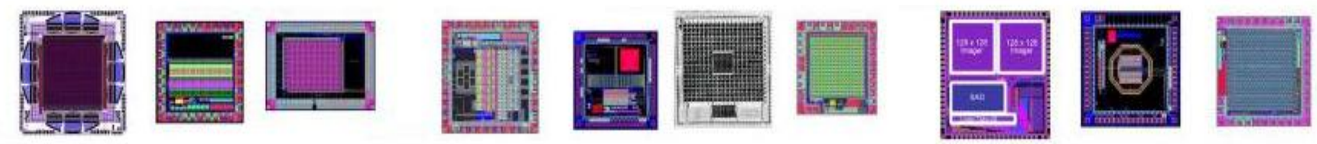
Discrete dynamical model: use lattice to model of surfaces (e.g. rubber, ice, wood) with tunable parameters to describe features

* normal distribution describes each parameter

* what happens to surface properties of material when values changed to mode region, tails of distribution?

Future Work – Neuromorphic CNS

Neuromorphic Systems:



A solution to modeling the brain that does not involve a neural network

Neuromorphic systems are hardware-oriented (deals explicitly with physical computation)

Requirements (representational):

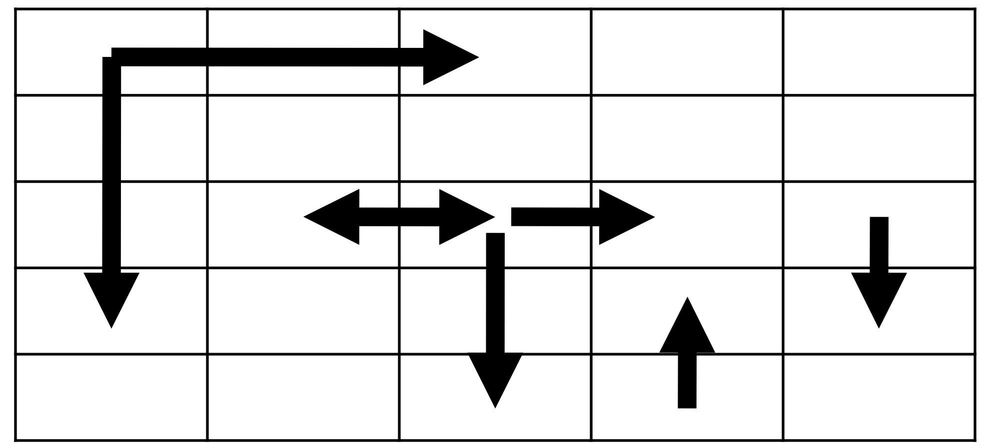
Selective long-range connectivity, scalable

Temporal (distributed) codes at multiple scales

Redundant and complex feature representation

Adaptable to needs of physical system

Hierarchical Cortical Grid



Inputs from surface units, actuators (muscles) to individual cells

Interactions between units (nearest-neighbor, proportion of non-local connections)

Scalable to n-dimensions (complexity)

Percolation, mean field models = memory (managed connectivity)