Towards Neurally Integrated High Degrees of Freedom Prosthetic Limbs

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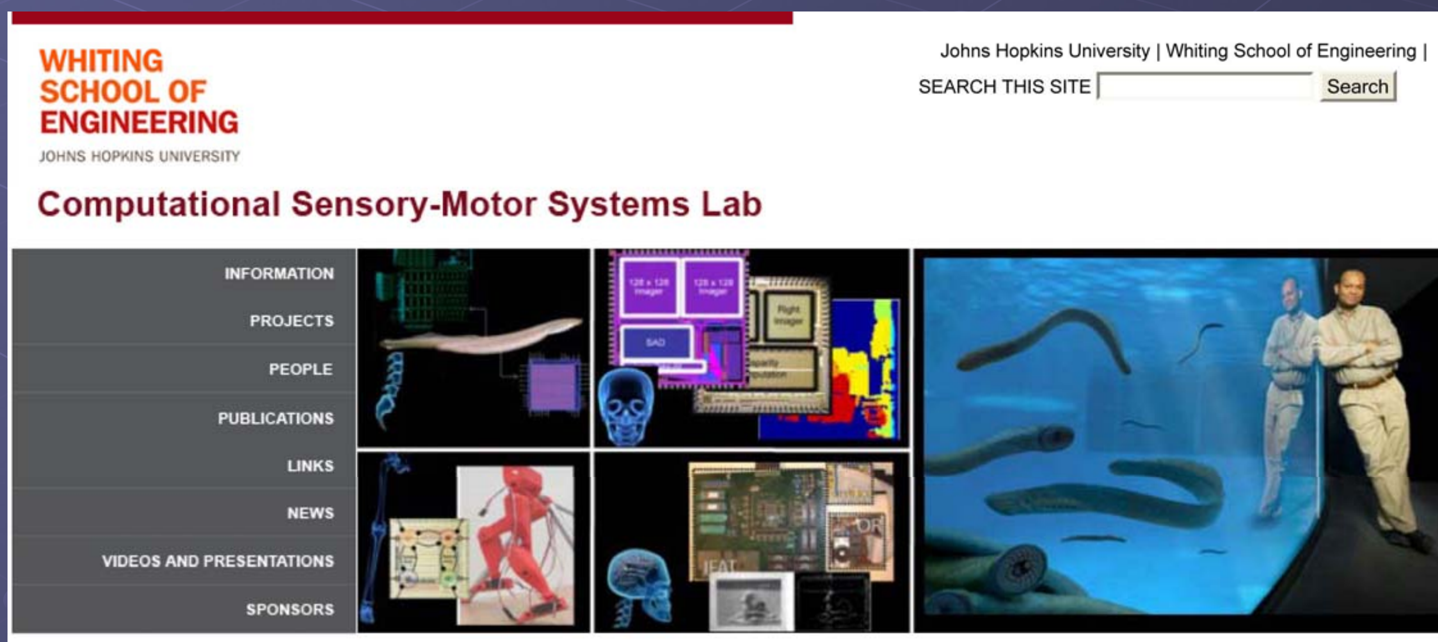

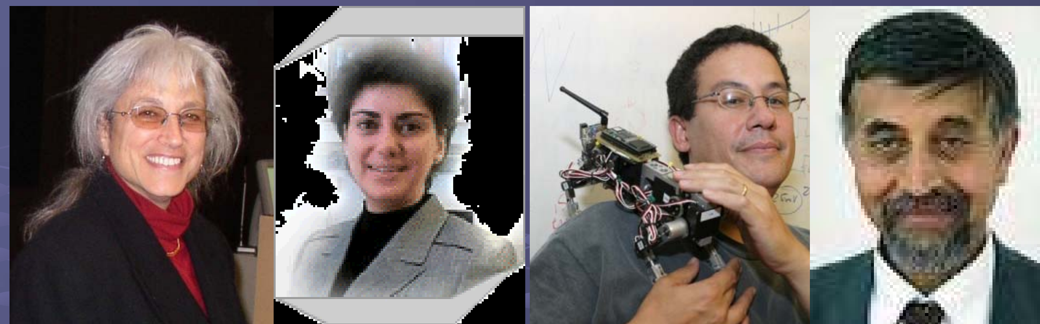

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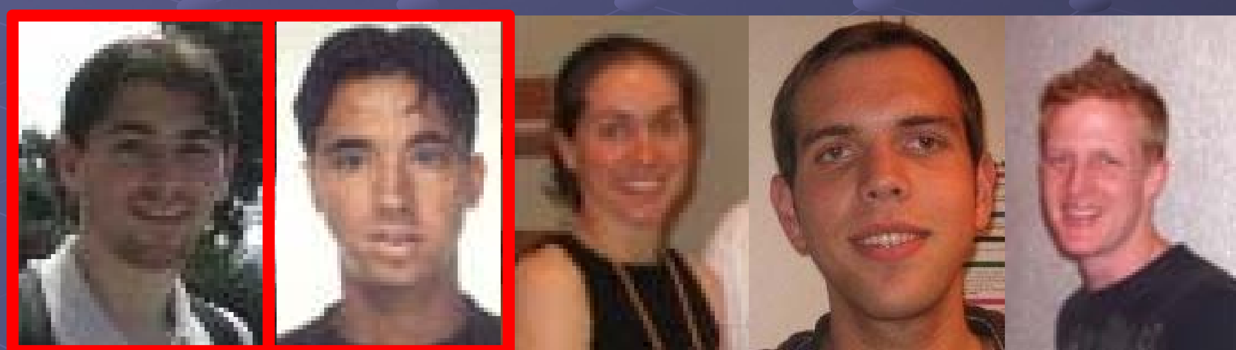

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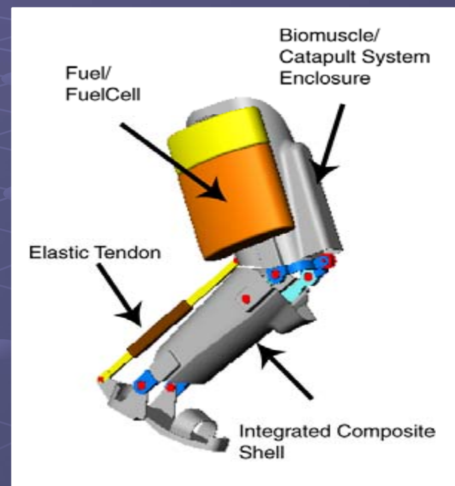
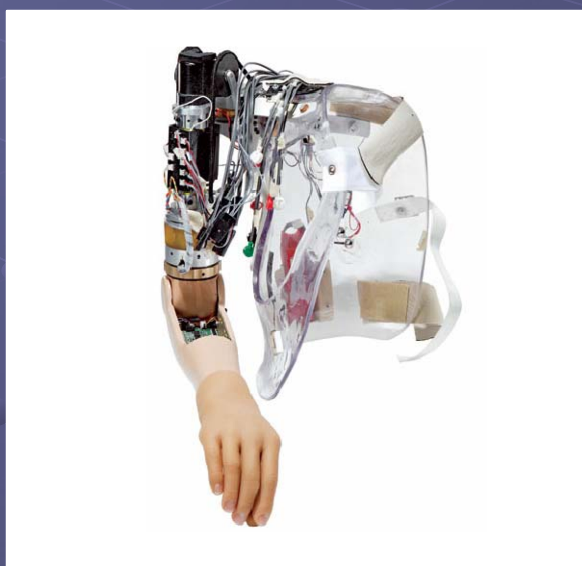
Sponsors:
NSF, NIH, ONR, DARPA, HMRC

The Big Picture: Motivation

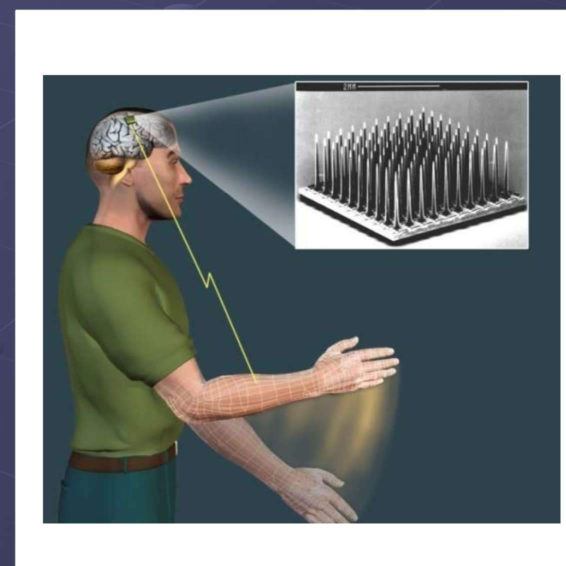
Developing Biomorphic Robotics





Restoring function after limb amputation

Adaptive Biomorphic Circuits & Systems



Restoring function after severe spinal cord injury

Presentation Outline

- Introduction
  - Central pattern generators
  - Are CPGs involved in upper limb control?
- Lower Limb Neural Prosthesis
  - Spinal cord injury and locomotion prosthesis
  - Gait controller: *silicon model of spinal cord circuits*
  - Phase controller: *controlling Behavior*
- Upper Limb Neural Prosthesis
  - High degree of freedom prosthetic hands
  - Decoding Arm EMG: *trans-radial prosthesis*
  - Decoding Motor Cortex: *individual finger movements*
- Conclusion and Future
  - Sensory feedback and haptics

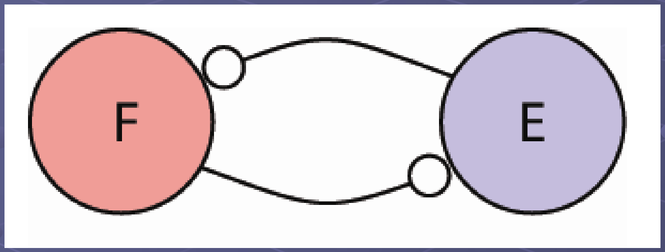
Central Pattern Generator (CPG)

- Networks of neurons in the spinal cord of vertebrates
- Generate sequences of patterned outputs to activate muscles
- Control motor systems with regular, periodic activity (breathing, chewing, locomotion, etc.)
- Basic architecture is preserved across species
  [Cohen et al., 1988]
- Basis of locomotion in all vertebrates studied to-date, including primates and humans*
  - Convincing evidence in marmosets [Fedirchuk et al., 1998]
  - Similar data in humans (without deafferentation) [Dimitrijevic et al., 1998]
- CPG is used for "*periodic*" not specialized, locomotion

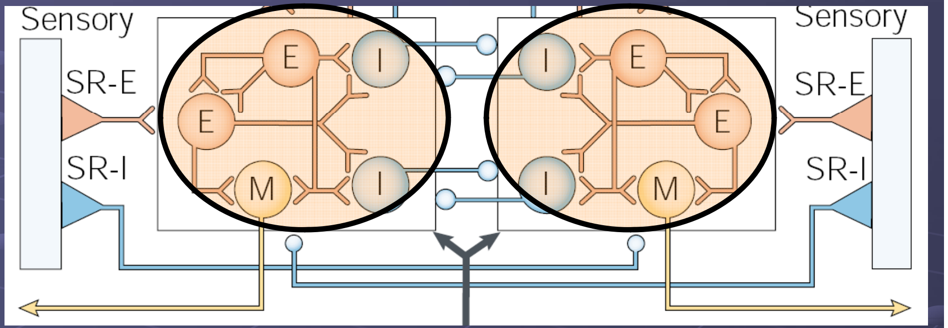
Source: J. M. Cleese, MPFC, 1970

CPG Architecture

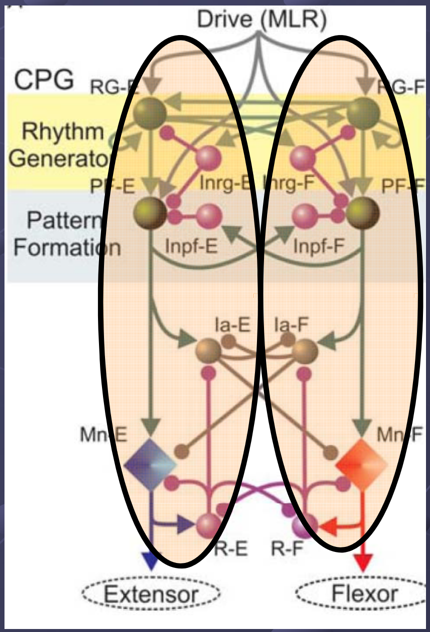
- First conceptual "model" in 1911 by T. G. Brown: half-center oscillator



- HCO structure preserved in modern models
- Cellular models in primitive vertebrates
- Models in higher vertebrates are less detailed; designed to match behavioral data

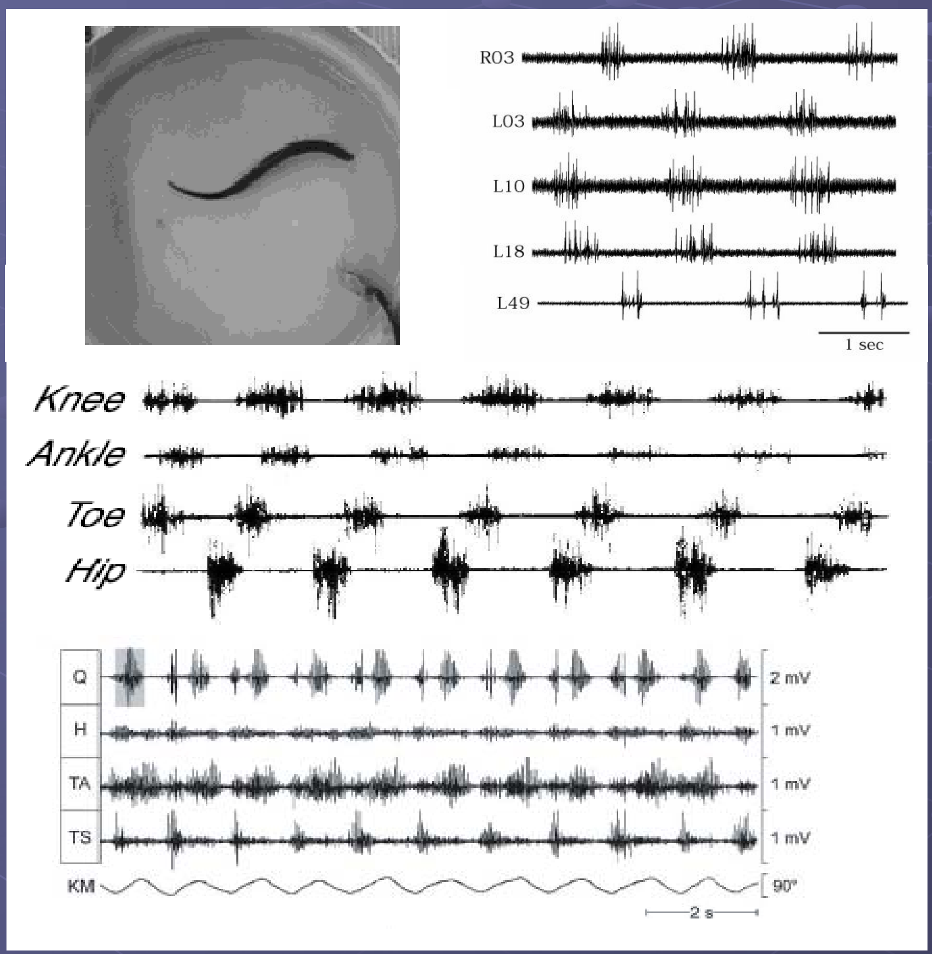


Source: Grillner, Nat Rev Neurosci, 2003

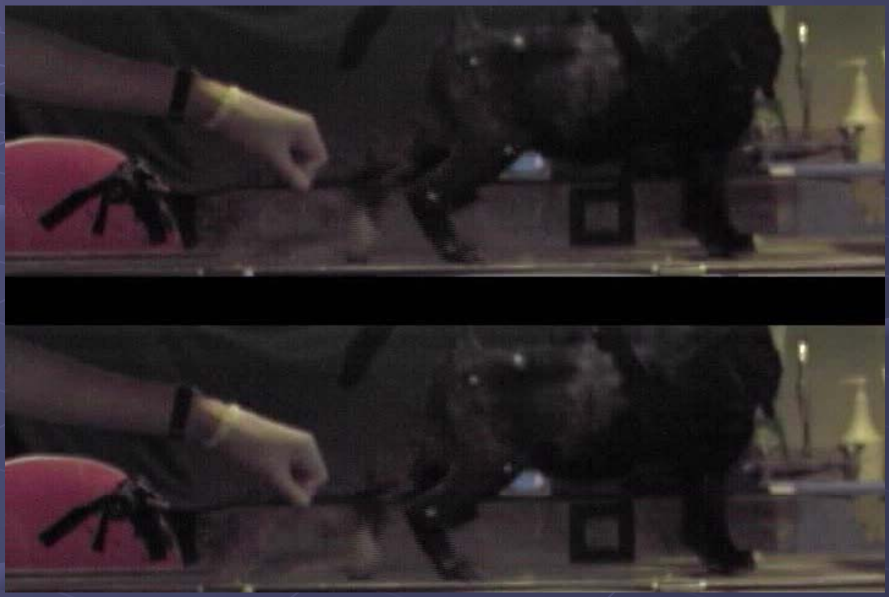


Source: Rybak et al., J Physiol, 2006

CPGs in Action



Source: Mellen et al., 1995;
Grillner & Zangger, 1984; Minassian et al., 2004



Spinal Transection @ T11

- The CPG is self-sufficient and contained within the spinal cord

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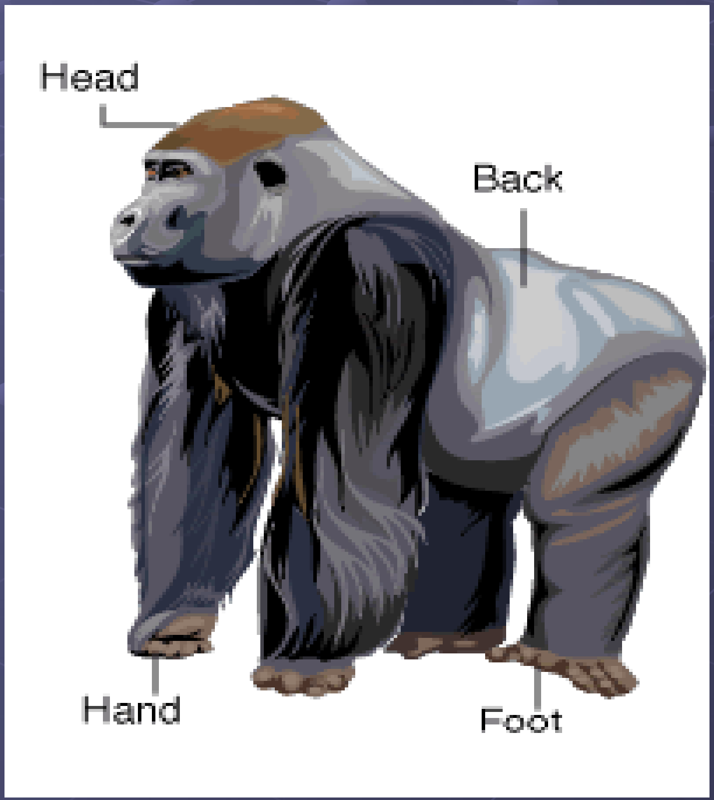
CPGs for arm movements

Question: “Does the CPG also effect upper limb movements?”



www.colszoo.org/animalareas/aforest/gorilla.html

CPGs for arm movements

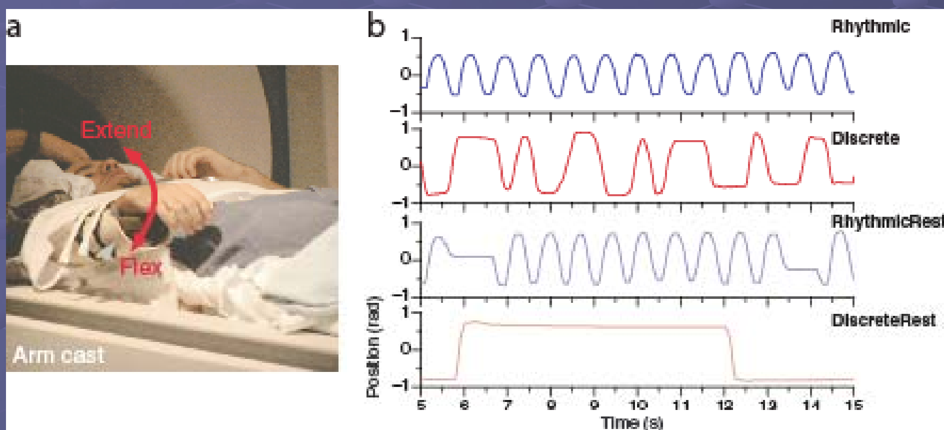
Question: “Does the CPG also effect upper limb movements?”

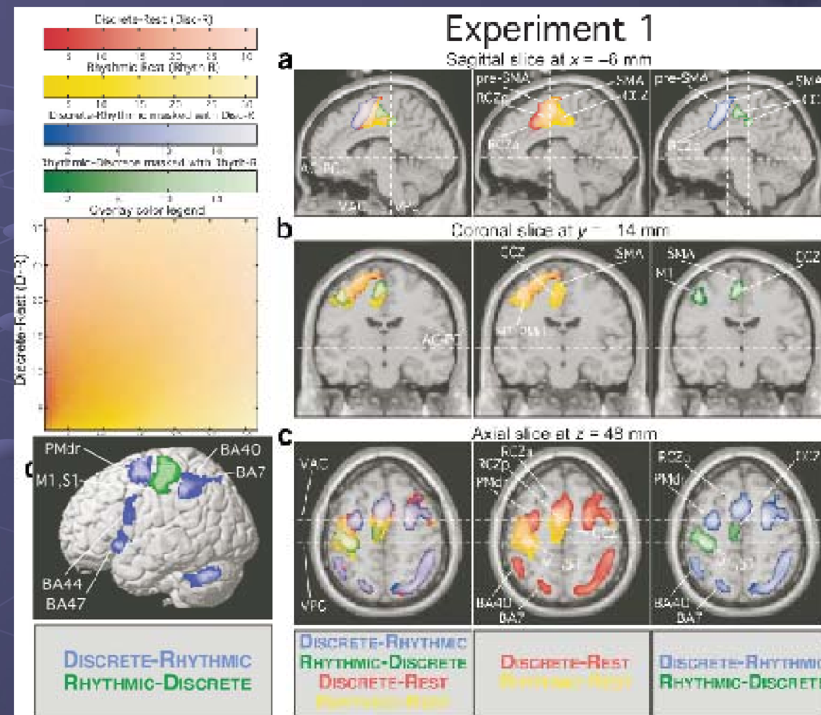
CPGs for arm movement

- Two philosophies:
  - Pattern-generation based models
  - Visually-guided trajectory formation models
- *Schaal et al.*: wrist flexion/extension experiments to compare Rhythmic and Discrete Activity (RA, DA)
  - ➔ Do the two types of movements have a common neural basis?

[Schaal, S., Sternad, D., Osu, R., Kawato, M. **Rhythmic arm movement is not discrete**. *Nature Neuroscience* **7**(10), 1137-1144 (2004)]

CPGs for arm movement





- Conclusion: "since the entire functional **rhythmic movement is contained in the discrete circuit**, it is possible that **discrete movement is based on modulating** the original pattern generator loop, for example by smoothly **aborting the rhythmic movement after half a cycle**"

[Schaal, S., Sternad, D., Osu, R., Kawato, M. **Rhythmic arm movement is not discrete**. *Nature Neuroscience* **7**(10), 1137-1144 (2004)]

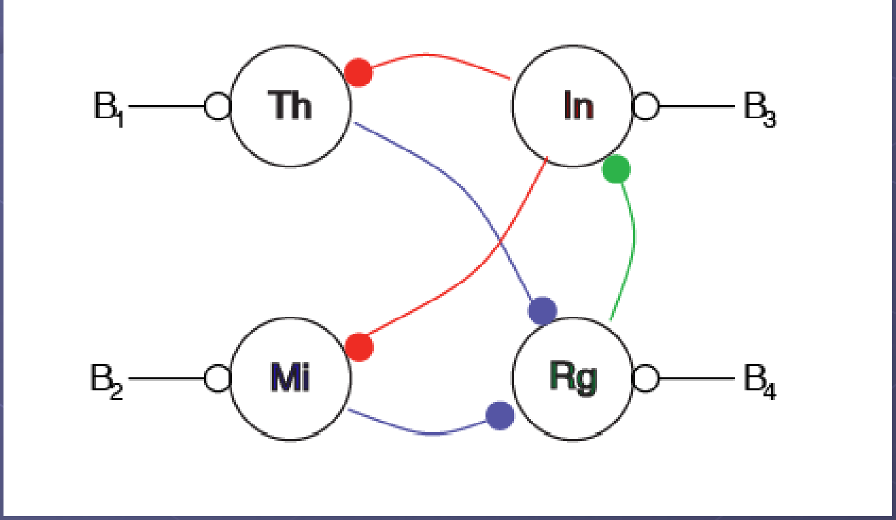
Repetitive Hand Motions

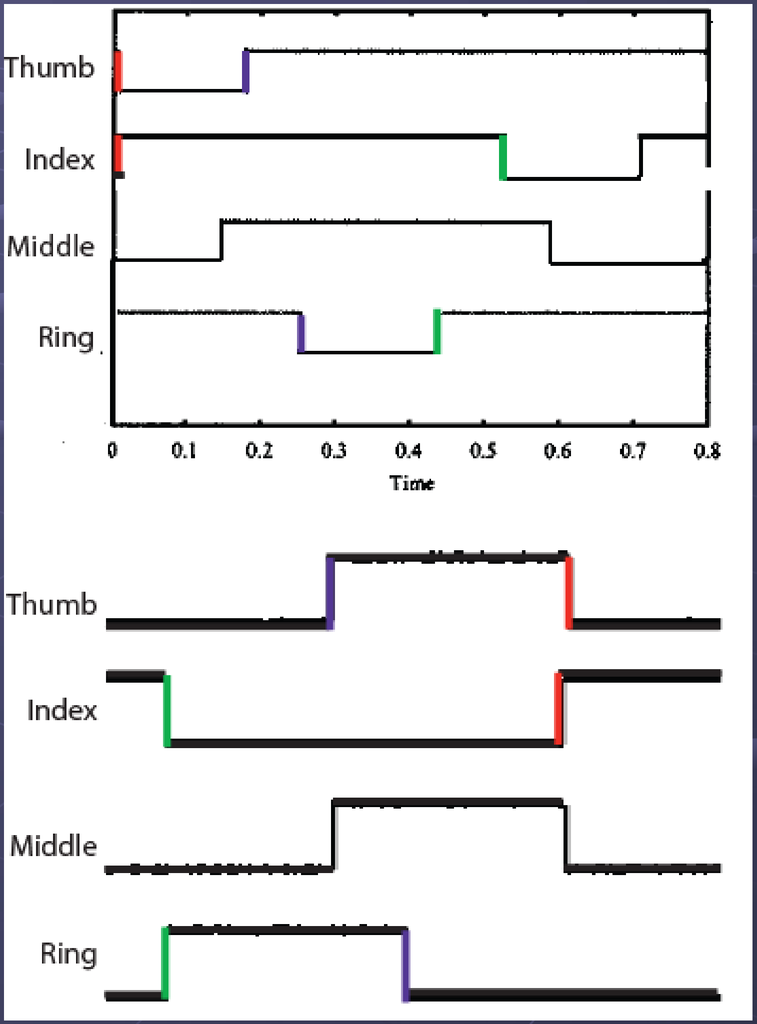
- Object rotation
- Force sensing resistors on object
- Study intrinsic relationships between fingers during task
- Organize contact patterns within a "period"

[Y. Kurita, J. Ueda, Y. Matsumoto, T. Ogasawara. CPG-based manipulation: generation of rhythmic finger gaits from human observation. *Proc.ICRA*, 2004.]

CPG implementation

- Index turns off thumb
- Thumb turns off ring
- Ring turns off index
- Middle and thumb in sync





[Russel, et al., EMBS, 2008]

Controlling upper limb movements

- it *is* possible to use CPG-based mechanisms to smoothly **abort the rhythmic movement after half a cycle**, as suggested by Schall
- This can be achieved on wrist movements as well as movements of individual fingers
- In amputees and tetraplegics: necessity to *first extract movement intention* as conveyed by CNS/PNS-related activity

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Spinal Cord Injury (SCI)

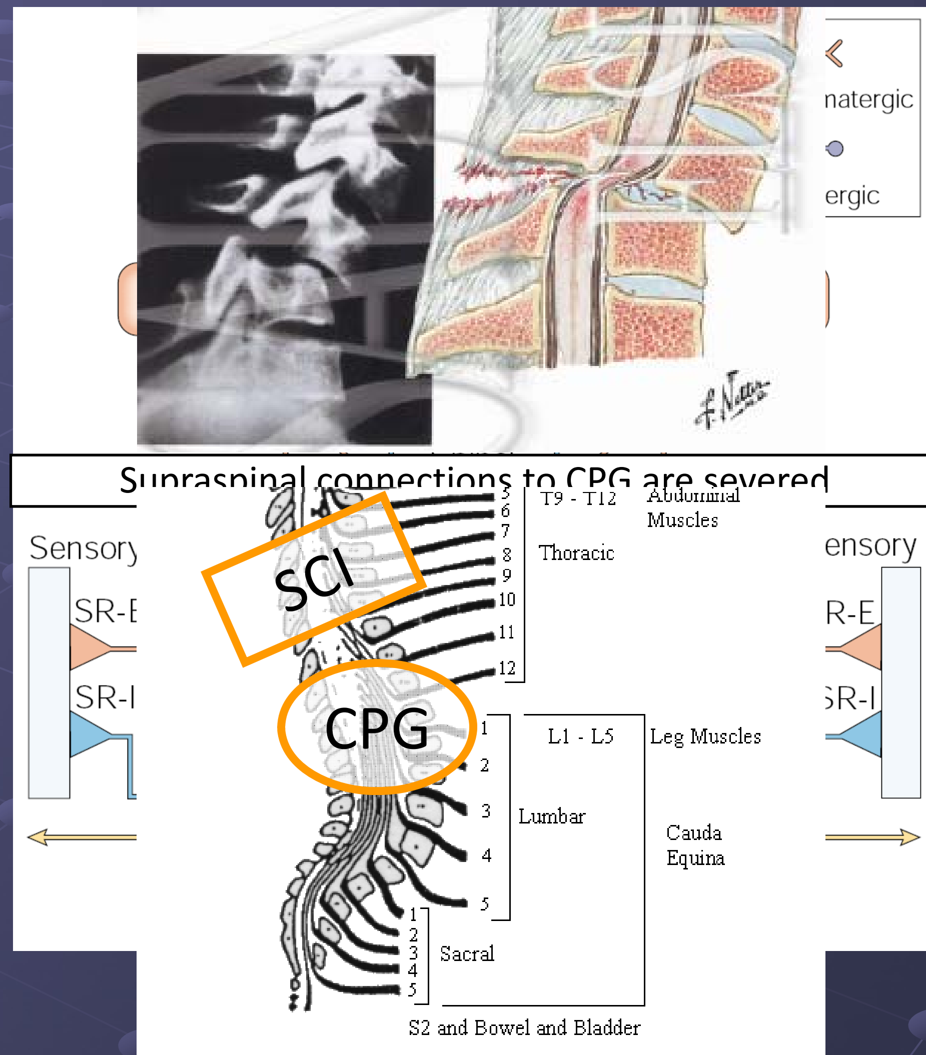
- SCI is usually a focal injury:

  vertebral body dislocation →

  spinal cord contusion

  - Kills spinal cord cells at lesion site
  - Severs connections
  - Leaves cells above/below lesion intact
- In most cases (~65%), lower limb CPG is intact after SCI
- Paralysis is caused by loss of descending control of the CPG, not by loss of CPG itself
  - Tonic & phasic inputs to CPG are disconnected
  - Efferent inputs required to activate CPG and control locomotion

  → Paralysis



Responsibilities of Locomotion Controller

1. Select Gait

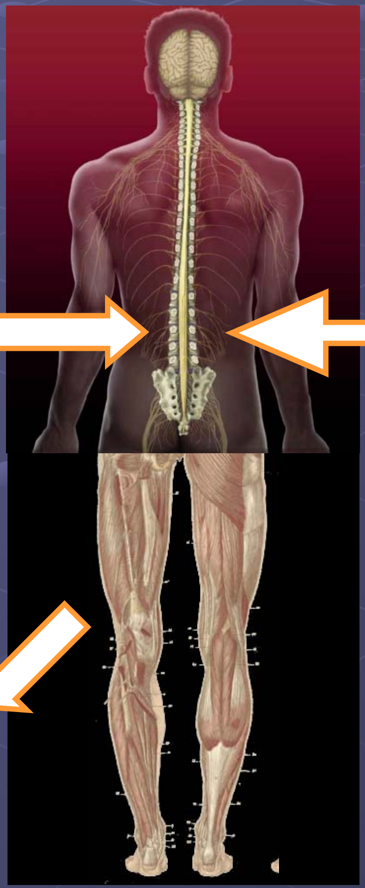
+ specify desired motor output
  - phase relationships
  - joint angles

4. Control Output of CPG

+ phasic stimulation (efferent copy required for precisely-timed stimuli)
  - convert baseline CPG activity into functional motor output
  - correct deviations
  - adjust individual components
  - adapt output to environment

3. Generate "Efferent Copy"

+ monitor sensorimotor state
  - external sensors on limbs
  - internal afferent recordings



2. Activate CPG

+ tonic stimulation initiates locomotion
  - epidural spinal cord stimulation (ESCS)
  - intraspinal microstimulation (ISMS)

Select gait ~ brain
Activate CPG ~ brainstem (MLR)
Efferent copy ~ efferent copy
Enforce/adapt output ~ phasic RS

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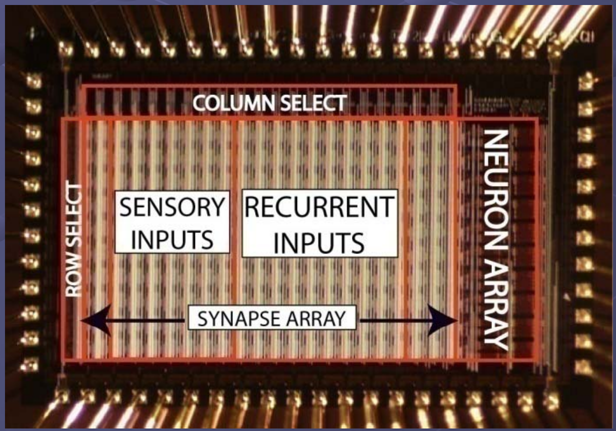
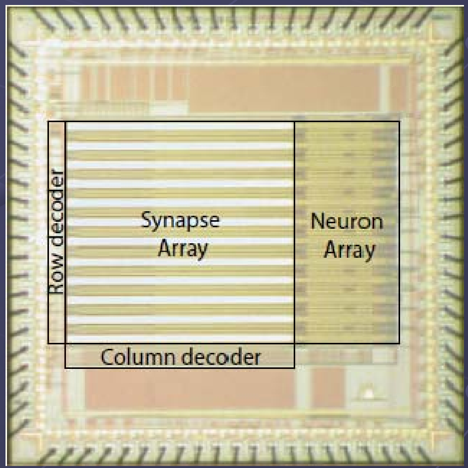
Hardware Development: Gait Controller

- Goal: develop a hardware system that can prescribe appropriate motor output based on pre-defined gait and current sensorimotor state
- Justification: need to know what the biological CPG is doing at all times and what we want it to do next in order to effectively control it
- Approach: build a silicon model of biological CPG, i.e. a neuromorphic silicon CPG chip (SiCPG)

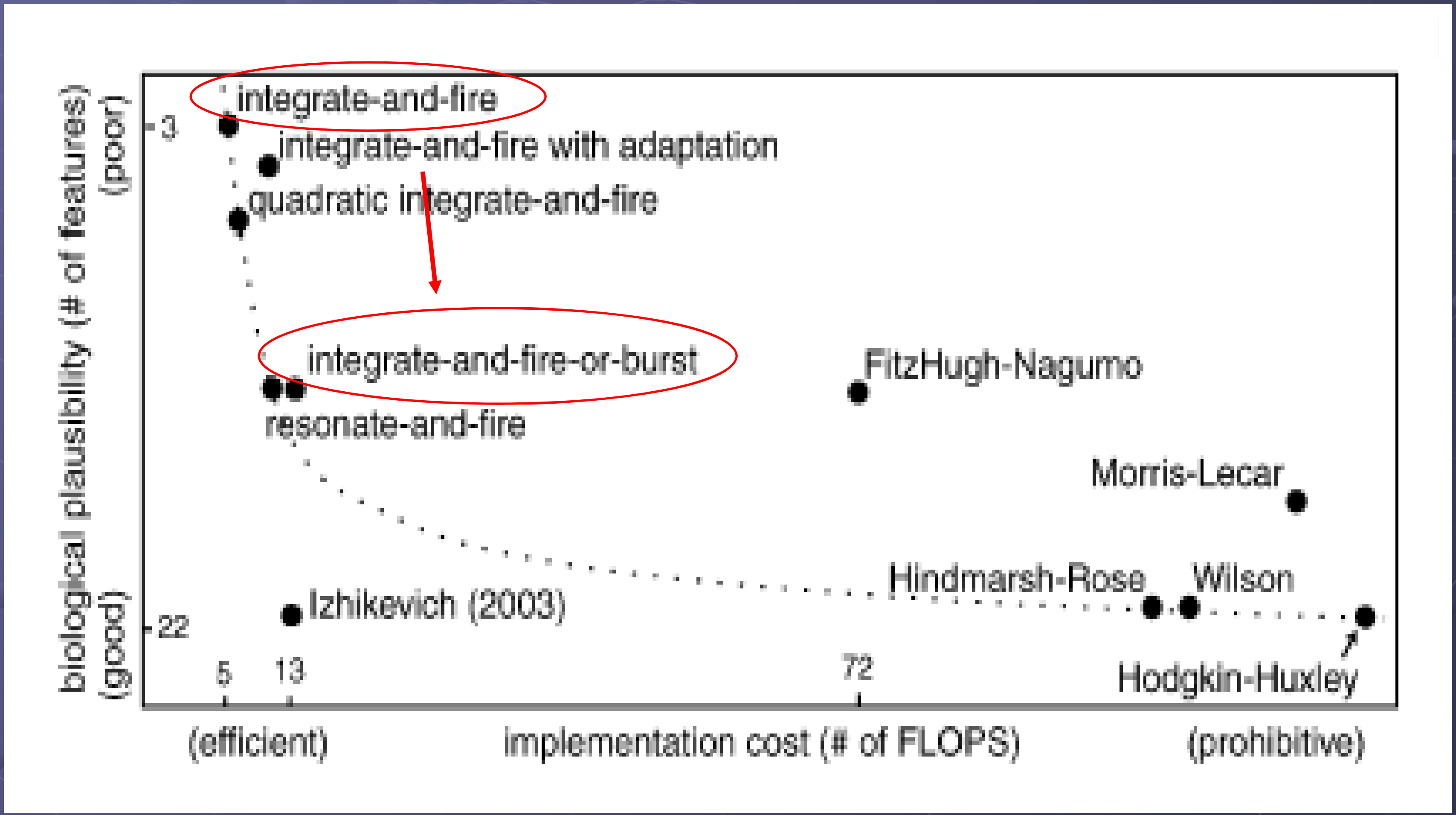


CPGv2 (Tenore et al., 2004)



CPGv3 (Tenore et al., 2006)

Approach: Neuromorphic Engineering

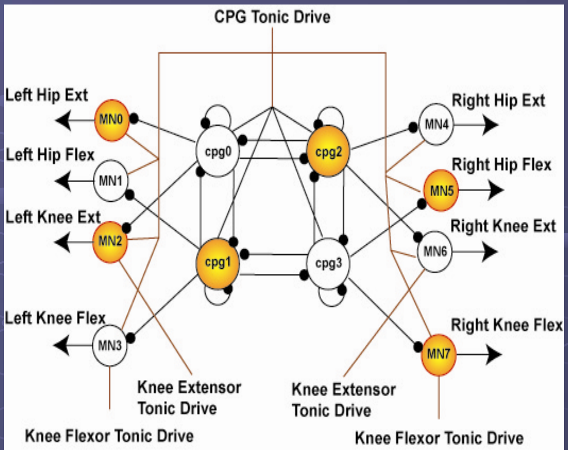


Mead, C. *Analog VLSI and Neural Systems* (1990)

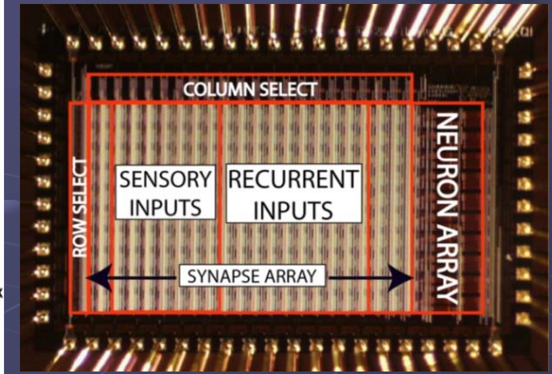
Izhikevich, EM. **Which model to use for cortical spiking neurons**?
IEEE Trans. Neural Networks, **15**:5, 1063-1070 (2004)

Robot + CPG Chip

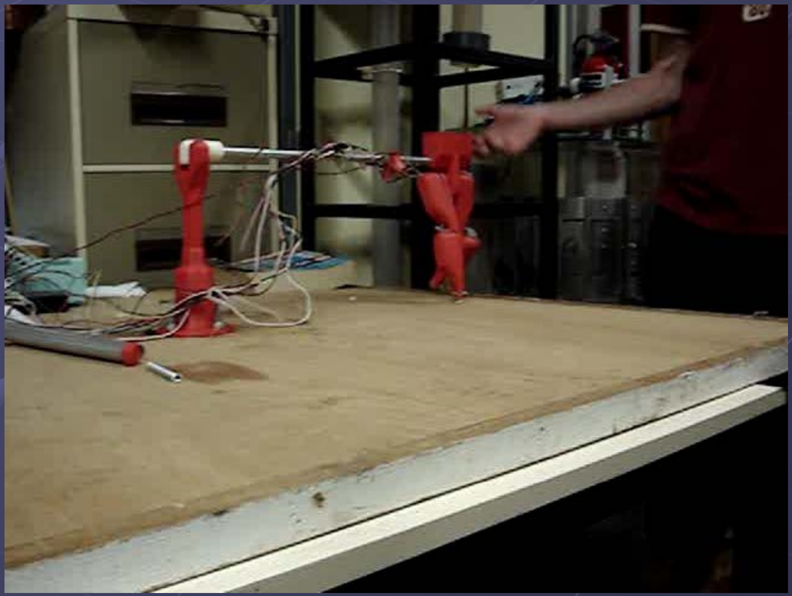
- Goal: Use artificial motor system to develop on-line phase control infrastructure (for future use in animal studies)
- Materials:
  - Partially-supported bipedal robot ("RedBot") or RoboCat
    - Servo motors actuate hips, knees, and ankles
  - Reconfigurable silicon CPG chip
    - CPG controls hip movements, knee/ankles are passive
- Strategy: Use same experimental design as lamprey preparation to test new hardware
  - Choose desired gait
  - Measure PDR of CPG chip
  - Apply stimuli at specific phases



Source: Lewis et al., 2005



Source: Tenore et al., 2004

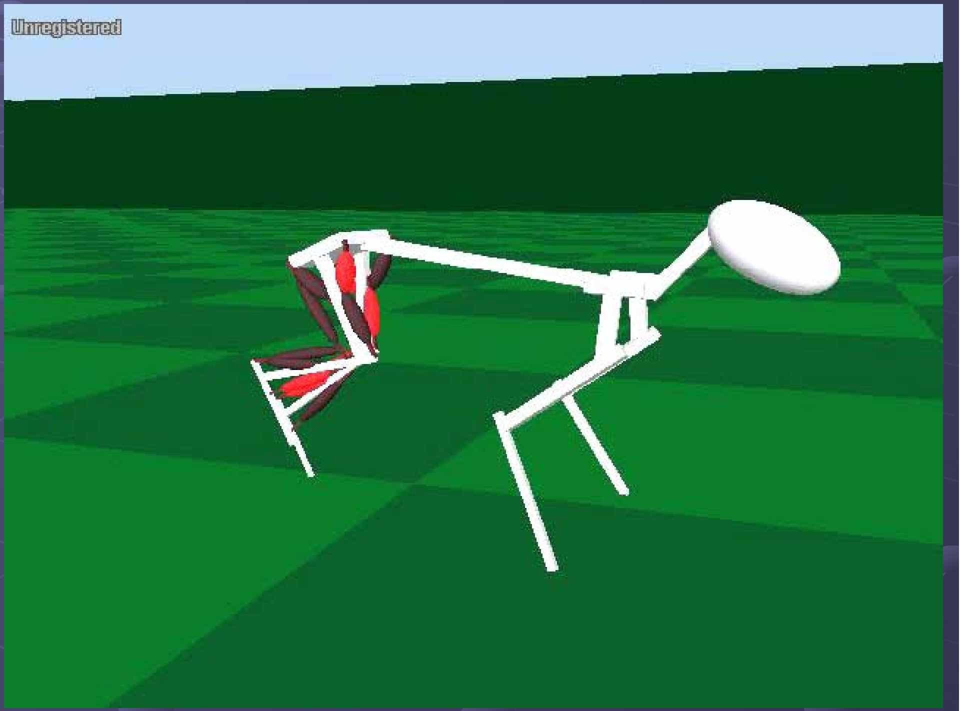


In Vivo Testing of SiCPG Gait Controller

- Goal: apply hardware to locomotion controller
  - Demonstrate that SiCPG can function as a Gait Controller *in vivo* (i.e. prescribe appropriate motor output in real-time based on pre-defined gait and current sensorimotor state: I.e. generate our "Efferent Copy")
- Procedure:
  - Design CPG network to produce forward walking; specify gait in terms of:
    - Phase relationships between muscles
    - Joint angles for swing, stance, etc.
  - Program CPG network onto SiCPG chip
  - Use external sensors on limbs to provide sensory feedback to SiCPG chip
  - Use output of SiCPG chip to control locomotion
- *For testing purposes, use intramuscular (IM) electrodes to stimulate muscles directly (not phasic CPG control)*
    - Causes rapid fatigue and has other problems, BUT...
    - Directly controlling all motor activity in closed-loop (by controlling the muscles) verifies that we can use the current state to prescribe appropriate motor output
      - Output of limbs ~ CPG activity (efferent copy)
    - Can be extended to phasic control of activated CPG

Cat Walking 101

- IF-THEN formulation of “rules” governing hind limb stepping in cats:
  - Stance-to-swing transitions:
    - *IF* ipsilateral hip is extended
    - *AND* ipsilateral limb is unloaded
    - *AND* contralateral limb is bearing weight
    - *THEN* initiate flexion in the ipsilateral limb
  - Swing-to-stance transitions:
    - *IF* ipsilateral hip is flexed
    - *THEN* initiate extension in the ipsilateral limb

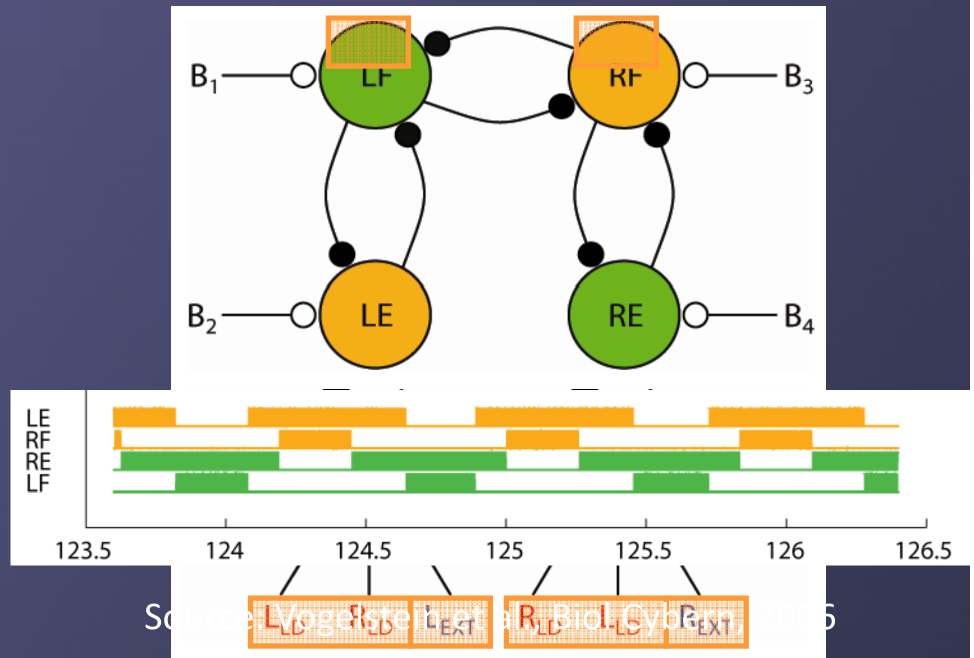


Source: Ekeberg and Pearson, J Neurophys, 2005

Source: Saigal et al., IEEE TNSRE, 2004; Prochazka, Can J Physiol Pharmacol, 1996; Guevremont et al., J Neurophys, 2007

Designing the Gait Controller's CPG Network

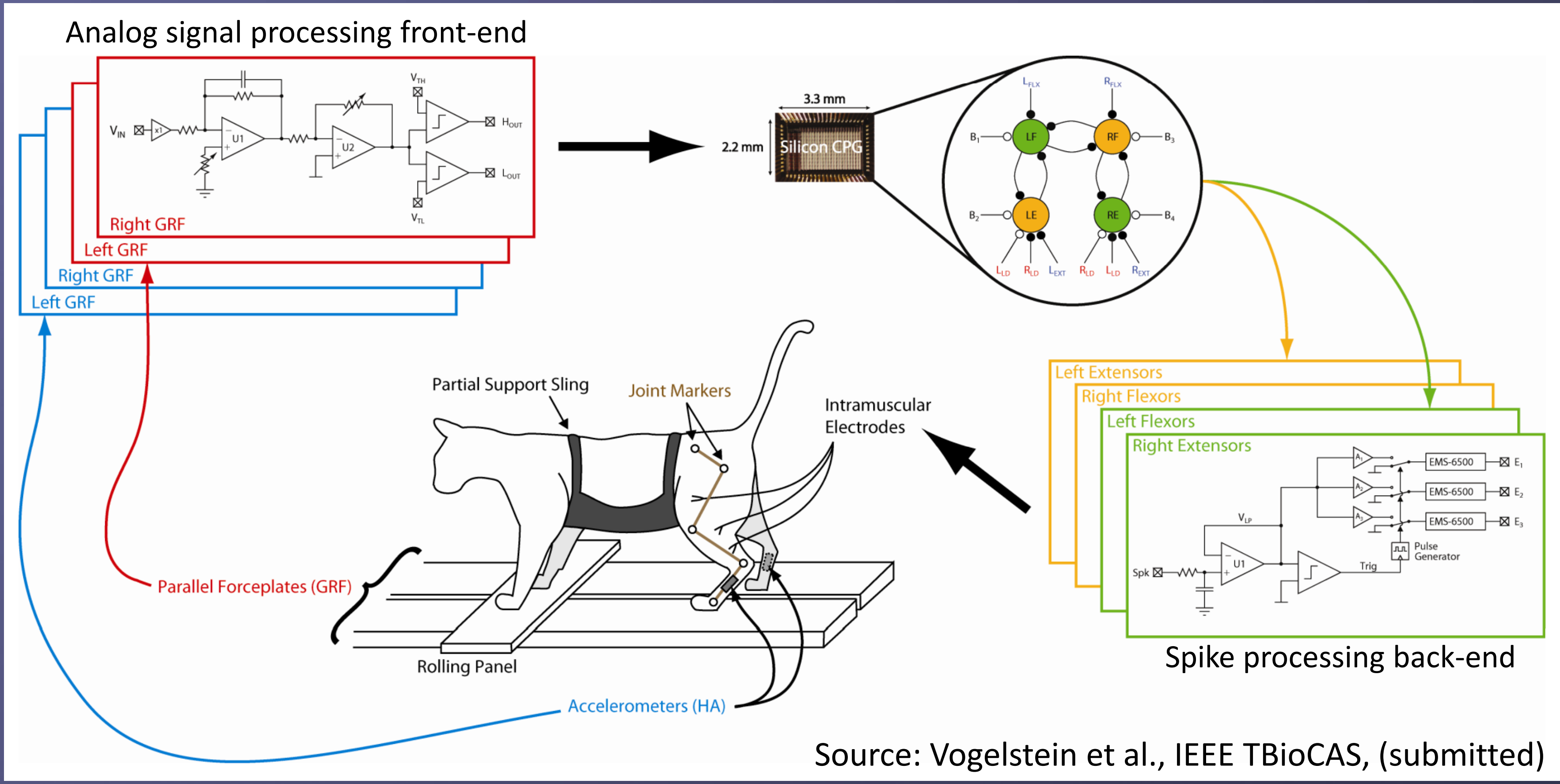
- Patterns in normal walking and IF-THEN formulation provides basis for CPG network
- Incremental design process, starting with the basics
  - Extensors and flexors are active in counterphase
  - Hindlimbs alternate between stance (extension) and swing (flexion) phases with roughly 70-30 duty cycle
  - Transitions from stance to swing and vice-versa are triggered by two main proprioceptive inputs
    - Hip angle: inputs indicate degree of left/right extension/flexion
    - Ankle load: inputs indicate degree of left/right loading
- Extensible: replace flexor and extensor neurons with hip/knee/ankle subpopulations
- Structure similar to biology-based models [Pearson, personal comm.]



Source: Vogelstein et al., IEEE TBioCAS (submitted)

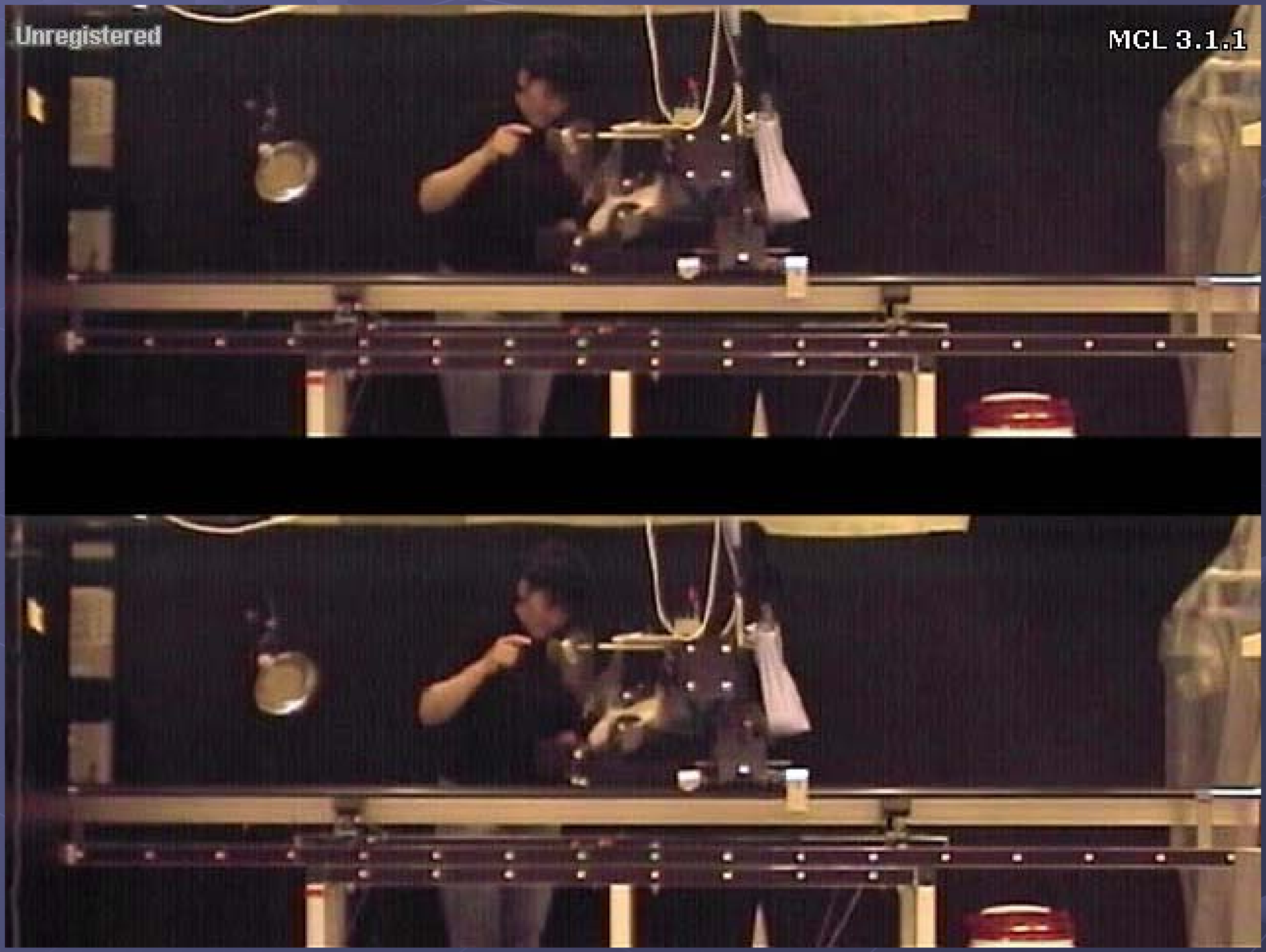
- Synaptic weights on bias, sensory, and lateral inhibitory inputs, along with rate of SFA, determine whether swing/stance (extensor/flexor) transitions are timed or sensory-driven
  - For these experiments, cats were allowed to walk at self-driven pace

Gait Control System



- 12 pairs of IM electrodes: 3 each for left/right hip, knee, and ankle extensors/flexors
- Two types of sensory data were collected for each leg
  - Hip angle (HA)
  - Ground reaction force (GRF)

Results: SiCPG Chip Controls Locomotion in a Paralyzed Cat



Source: Vogelstein et al., IEEE TBioCAS (accepted)

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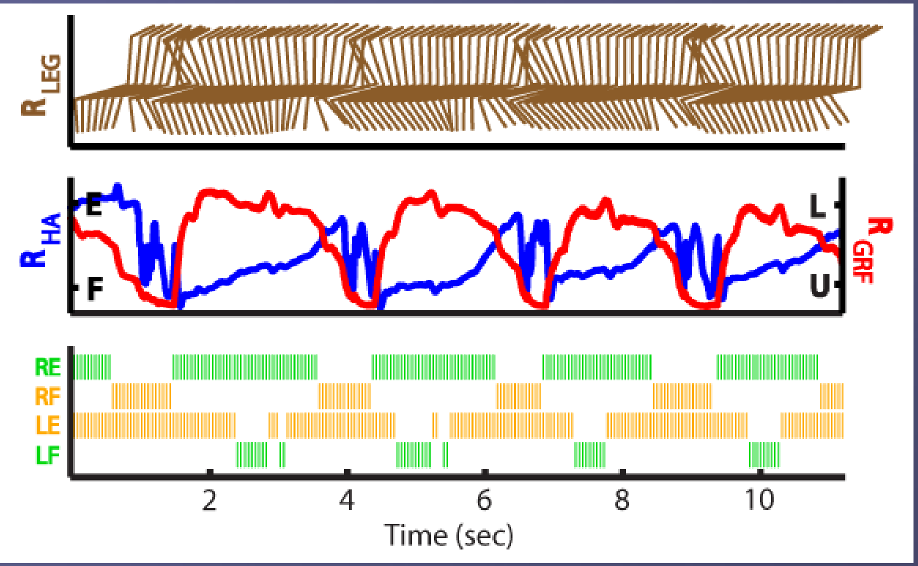

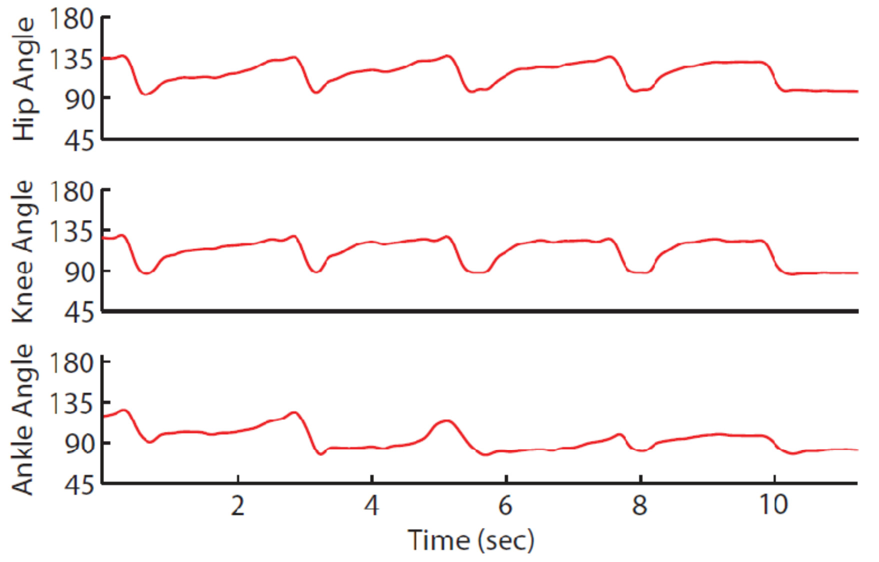

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Responsibilities of Neuroprosthesis

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+ specify desired motor output
  - phase relationships
  - joint angles

2. Activate CPG

+ tonic stimulation initiates locomotion
  - epidural spinal cord stimulation (ESCS)
  - intraspinal microstimulation (ISMS)

4. Control Output of CPG

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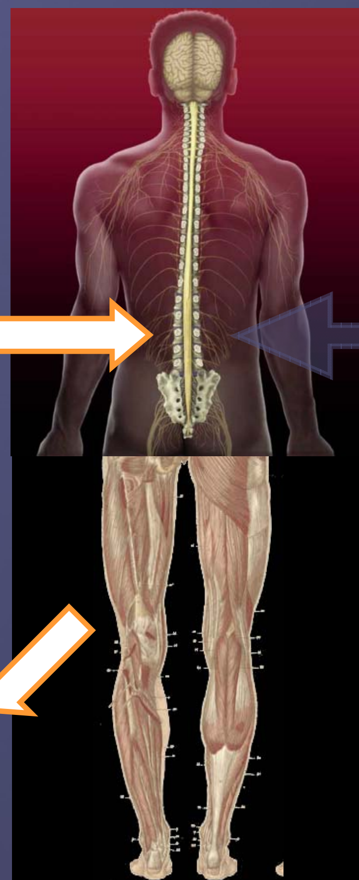
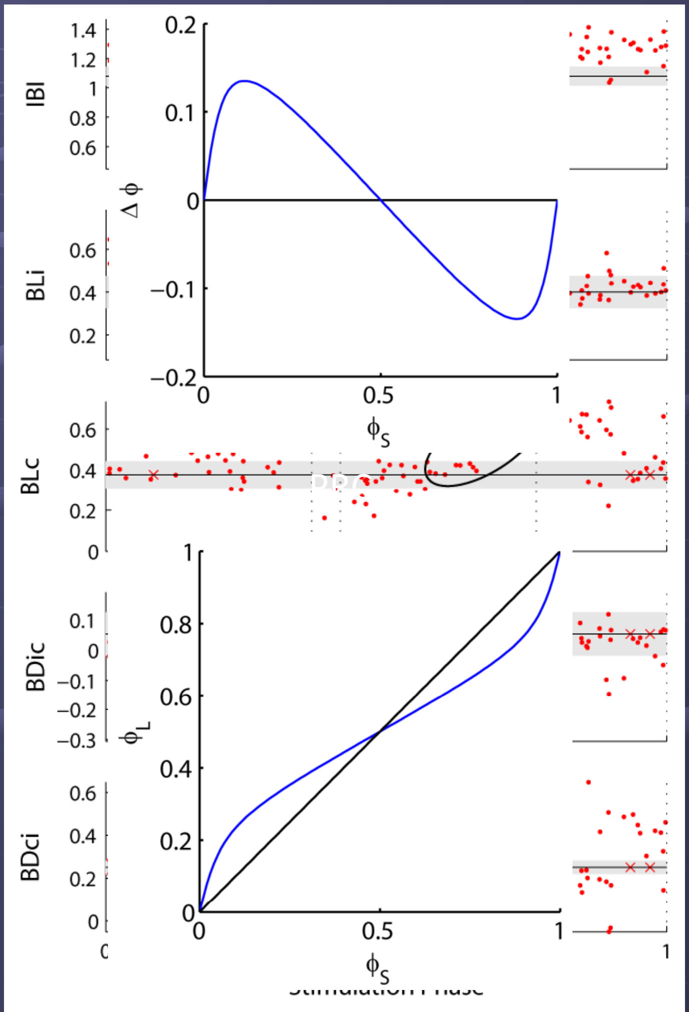


3. Generate "Efferent Copy"

+ monitor sensorimotor state
  - external sensors on limbs
  - internal afferent recordings

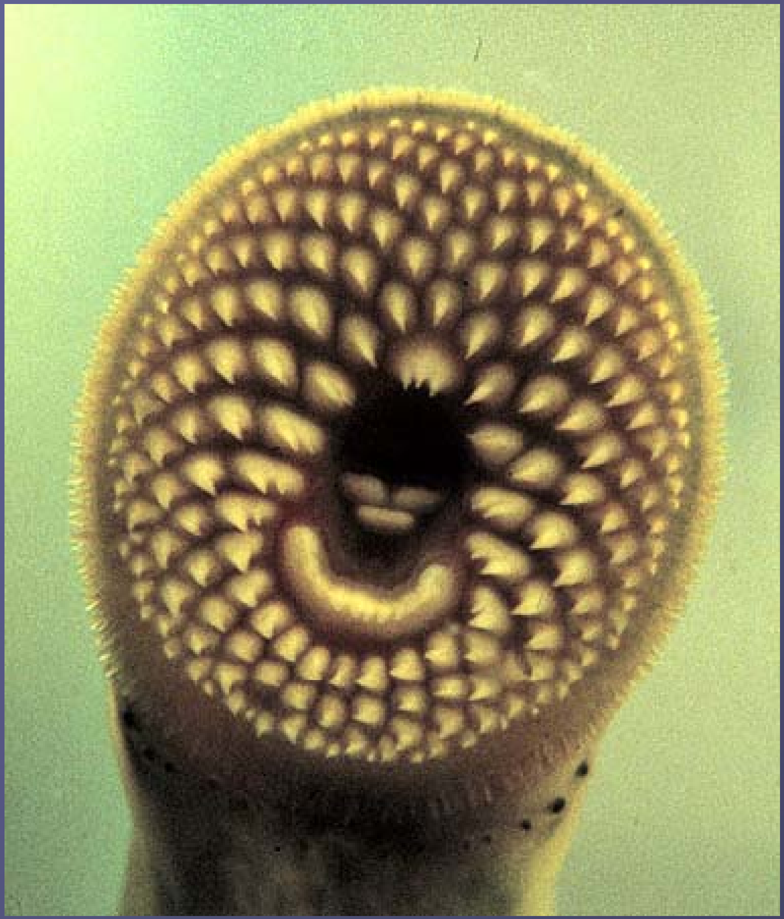
Nonlinear Oscillators 101

- Standard techniques:
  - Phase-response curve (PRC)
  - Phase-transition curve (PTC) aka Poincaré map
- Our technique: phase-dependent response (PDR) plots
  - Advantage: simultaneously illustrates effects of stimulation on any observable output of the nonlinear system (no state variables necessary)
  - Descriptive: illustrates how stimulation affects all relevant output dimensions
  - Prescriptive: specifies when to stimulate to achieve specific output



PTC

Lamprey 101

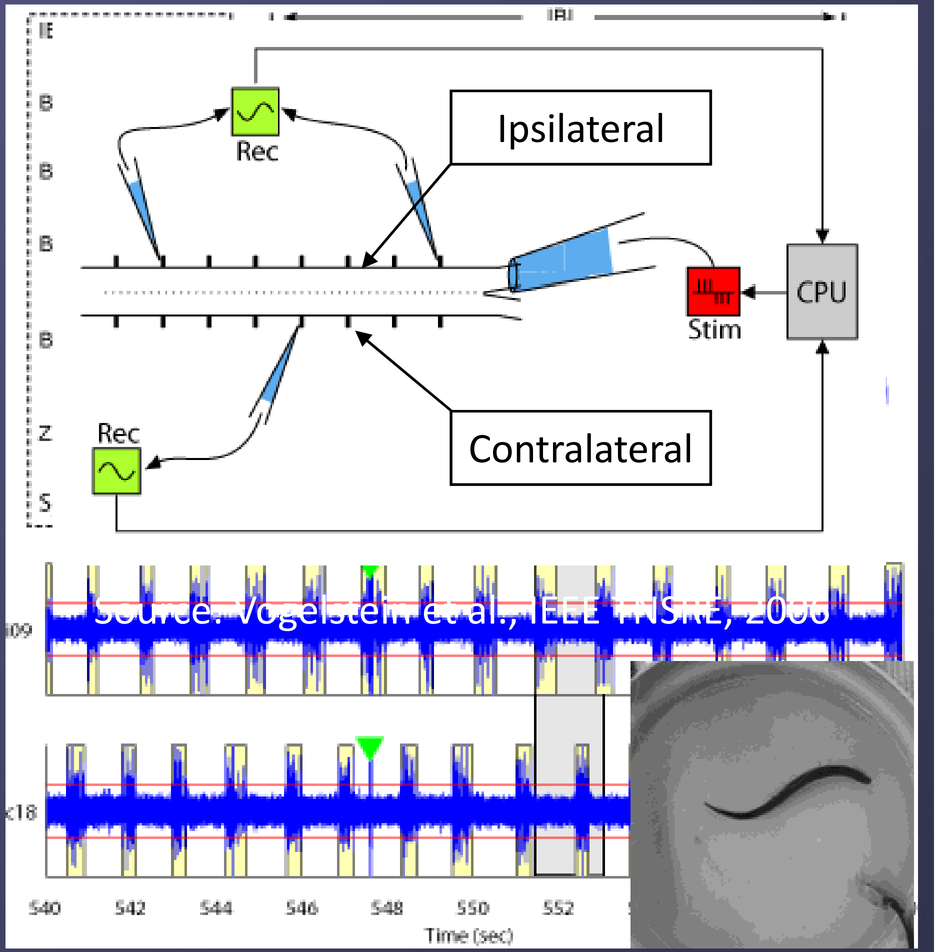


Business end of a lamprey

Lamprey-related casualty

CPG as Nonlinear Oscillator

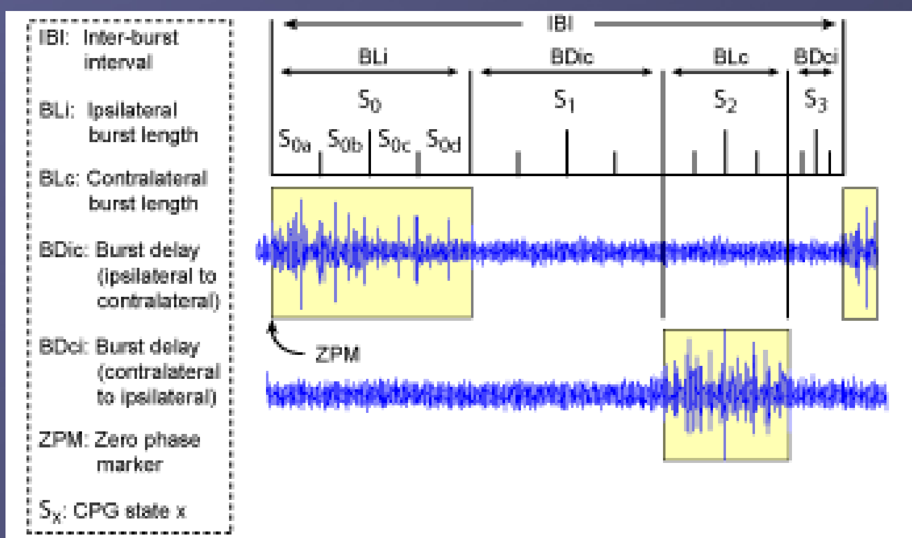
- Specific experimental protocol
  - Excise spinal cord
  - Initiate CPG activity with bath application of D-glutamate: “fictive swimming”
  - Record motor outputs on ventral roots
  - Apply suction electrode for stimulation at rostral end
  - Stimulate at 100 phases throughout CPG cycle
  - Measure effects of stimulation on all parameters of fictive locomotion as functions of phase (PDR)
    - Cycle period (IBI)
    - Burst length (BLi, BLc)
    - Burst delay (BDic, BDci)

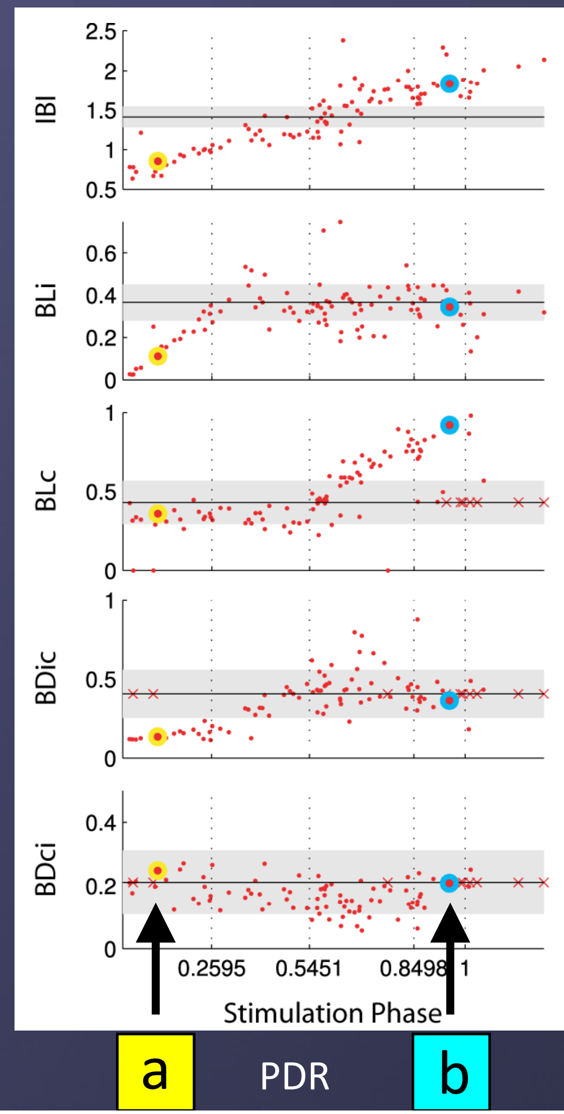


Source: Vogelstein et al., IEEE TNSRE, 2006

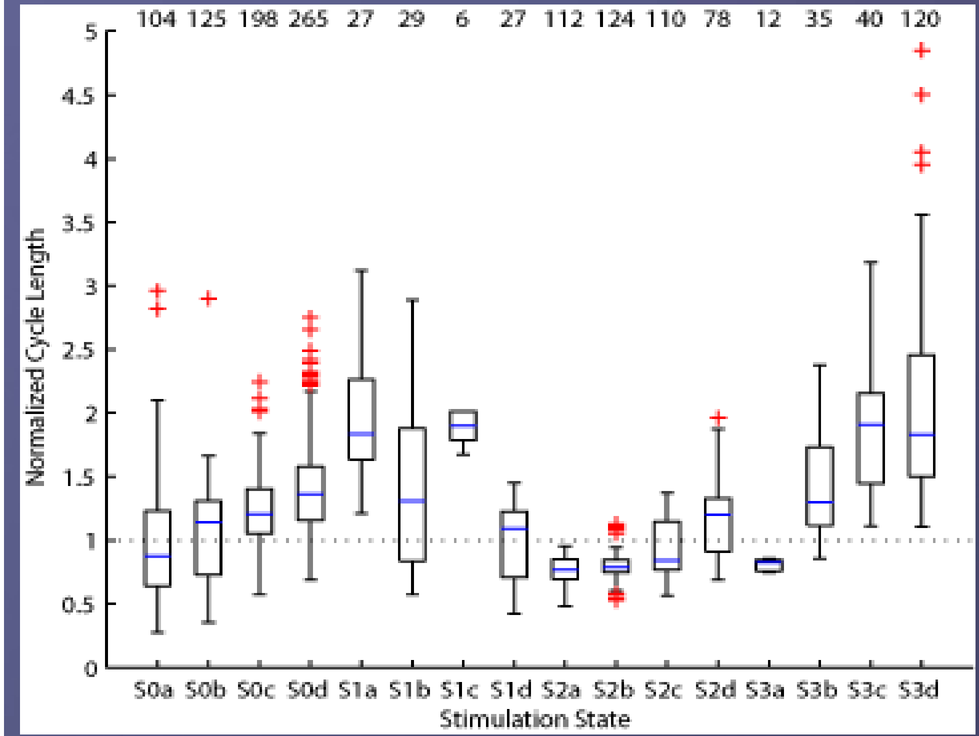
PDR Characteristics of Lamprey Spinal Cord

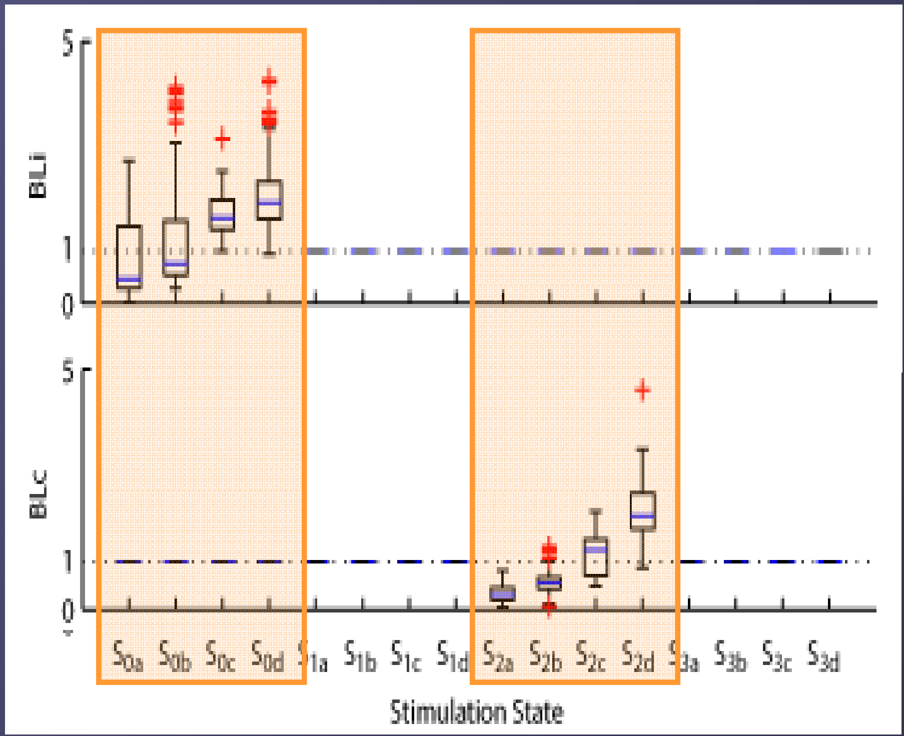
- Results from one experimental trial (PDR plot)
    - X-axis: Stimulation phase (%)
    - Y-axis: Measured burst parameter
    - Same stimulus applied at 100 different phases
    - Effects of each stimulus are plotted on all 5 axes





Results: Summary





Cycle Length dependent on stimulation phase

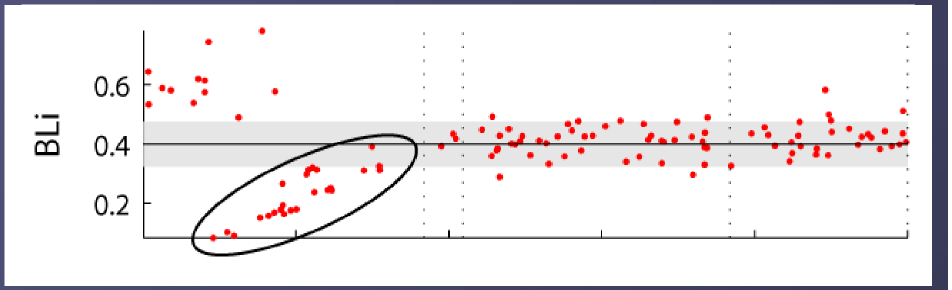
Burst Length and Delay are Independently controlled & limited in time

Source: Vogelstein et al., IEEE TNSRE, 2006

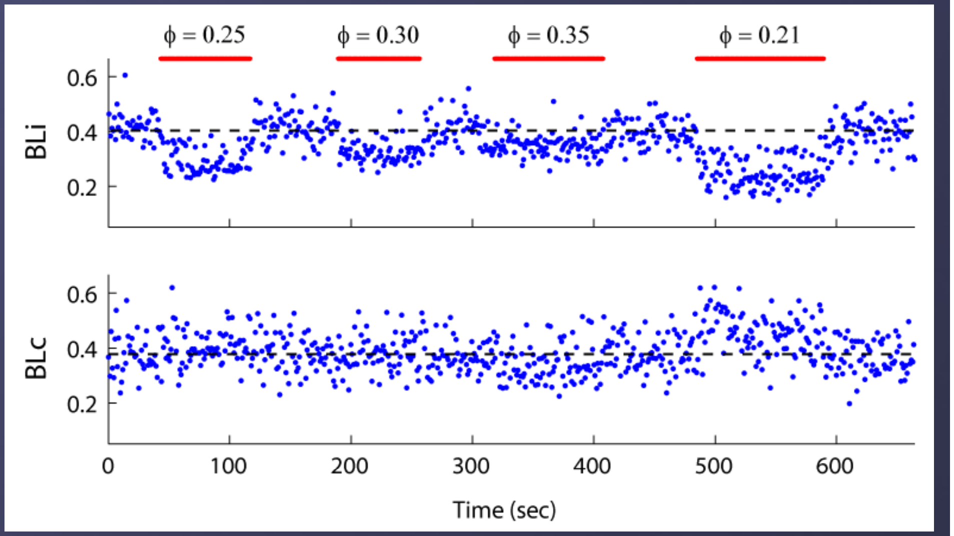
Results: Control of Ipsilateral Burst Length

Φ	Predicted BLi	Actual BLi
0.25	0.28	0.29
0.30	0.34	0.33
0.35	0.40	0.35
0.21	0.23	0.25

- Applied stimuli each cycle at specified phase for approximately 100 cycles
- Desired results
    - Predictable effects
    - Stable responses
    - No permanent shifts
    - Interaction between BLi and BLc at some phase/amplitude combinations



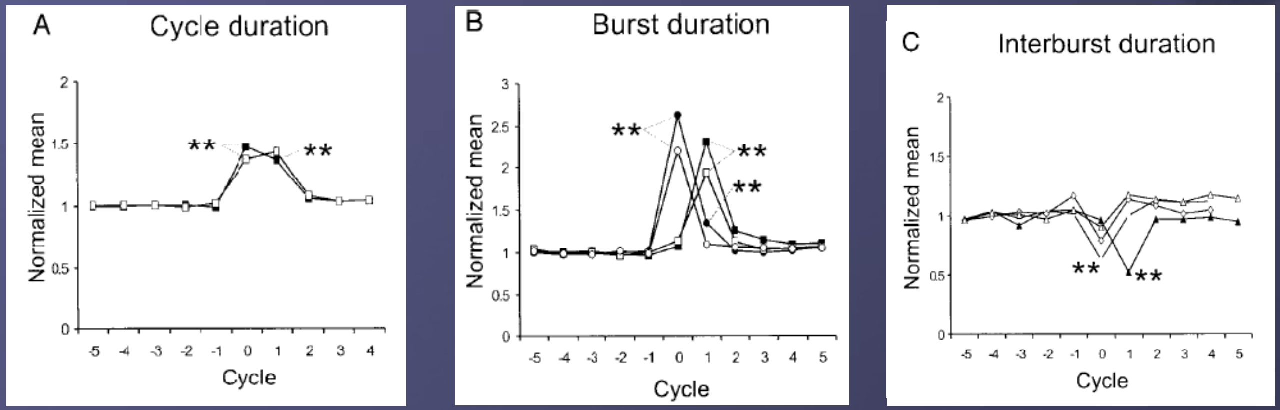
$$\text{BLi} = 1.24\phi - 0.03 \text{ (seconds)}, \; R^2 = 0.79, \;\; \phi \in [0.1, 0.35]$$



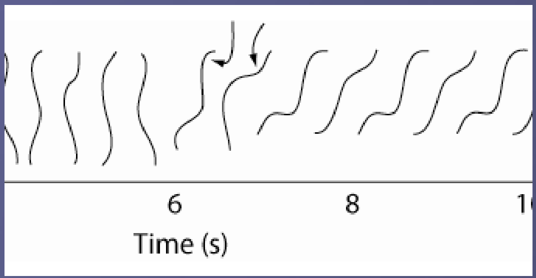
Source: Vogelstein et al. (in preparation)

Results: Steering Swimming

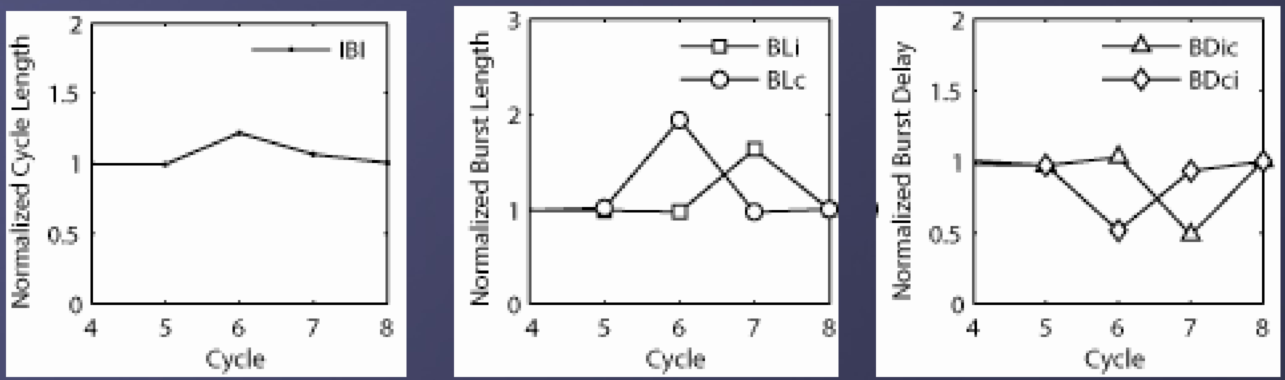
CPG/motor output during normal, brain-controlled turning (via phasic RS input)



Source: Fagerstedt & Ullen, 2001



Neuroprosthetic control via external stimulation (average effects)



Source: Vogelstein et al., 2006

- Conclusion: locomotion controller can functionally replicate output of natural neural control system through phasic spinal cord stimulation

Presentation Outline

- Introduction
  - Central pattern generators
  - Lower Limb and Upper Limb CPGs (?)
- Lower Limb Neural Prosthesis
  - Spinal cord injury and Spinal Prosthesis
  - Gait controller: *Silicon model of spinal cord circuits*
  - Phase controller: *Controlling behavior*
- Upper Limb Neural Prosthesis
  - High degree of freedom prosthetic hands
  - Decoding Arm EMG: *Trans-radial prosthesis*
  - Decoding Motor Cortex: *Individual Finger Movements*
- Conclusion and Future
  - Sensory Feedback and Haptics

Control paradigm

- Acquisition of electrophysiological signals involved in generation of movement
- Extraction of movement-related information from biosignals

So if something like this should happen to you
Ideally we'd want to get here
(sample source)

Source: 20th Century Fox, LucasArts
Thanks to: Kyle Fritz

State-of-the-art of Prosthetic Hands




JHU/APL RP2009 Prototype II Hand

Presentation Outline

- Introduction
  - Central pattern generators
  - Lower Limb and Upper Limb CPGs (?)
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  - Gait controller: *Silicon model of spinal cord circuits*
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- Conclusion and Future
  - Sensory Feedback and Haptics

Upper limb prostheses

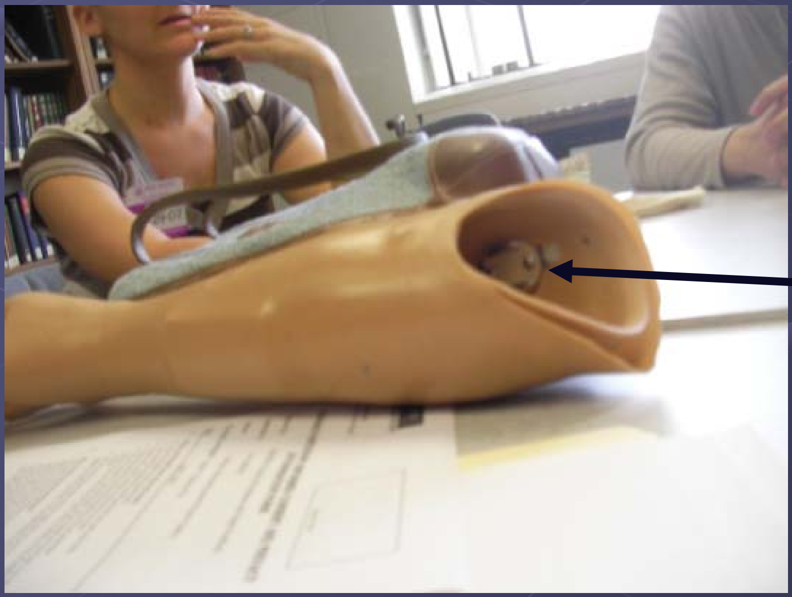
- Differences dependent on amputation level:
  - amputations distal to the wrist
  - *transradial*
  - elbow disarticulation/transhumeral
  - shoulder disarticulation

EMG Controlled Upper Limb Prosthesis

- Typical option for transradial amputees
- Traditional control schemes typically provide 2 *degrees of freedom* (DoF)
  - Hand open/close
  - Wrist pronate/supinate
  - Insufficient for dexterous manipulation tasks and control over individual fingers

Upper limb control

- Control signal provided by 2 non-invasive surface EMG electrodes broadly placed over each side of residual limb's extensor and flexor muscles
- To switch between two DOFs requires co-contraction of flexors and extensors



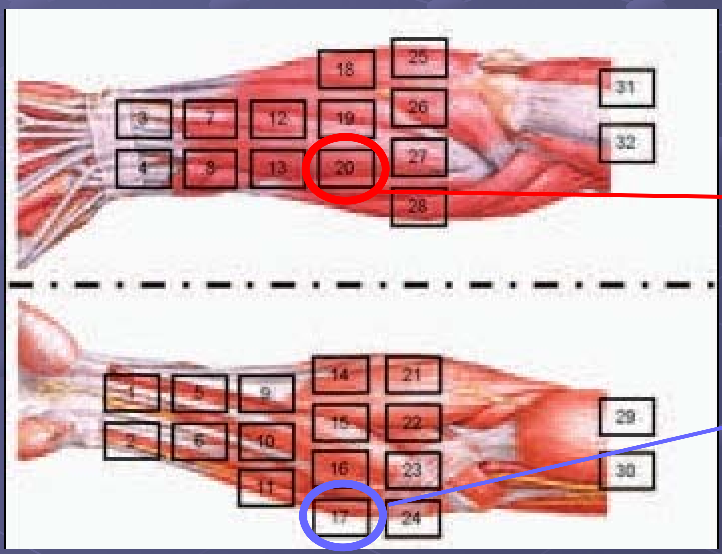
"Extensor" electrode

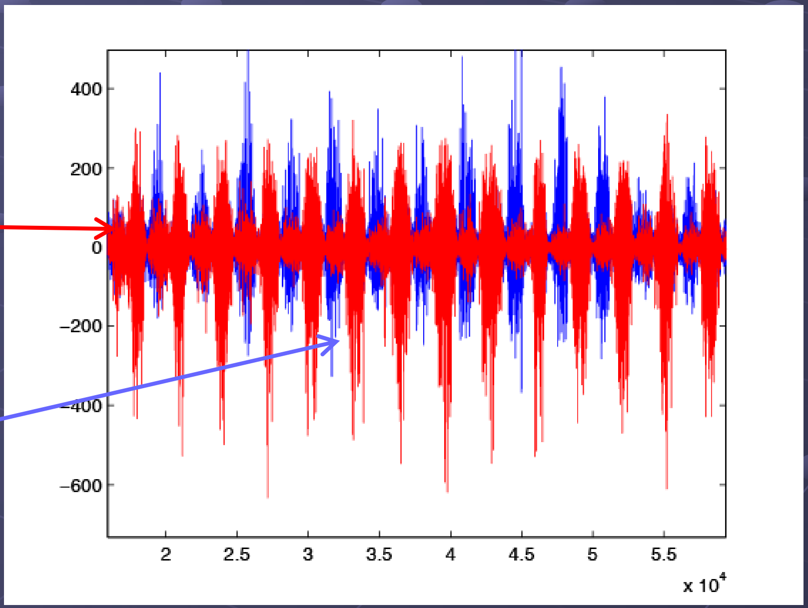
Acquisition of electrophysiological signals

- Invasive:
  - Neural signals from CNS (Spikes, LFPs)
  - Neural signals from PNS
  - Intramuscular EMG (IMES, BION)

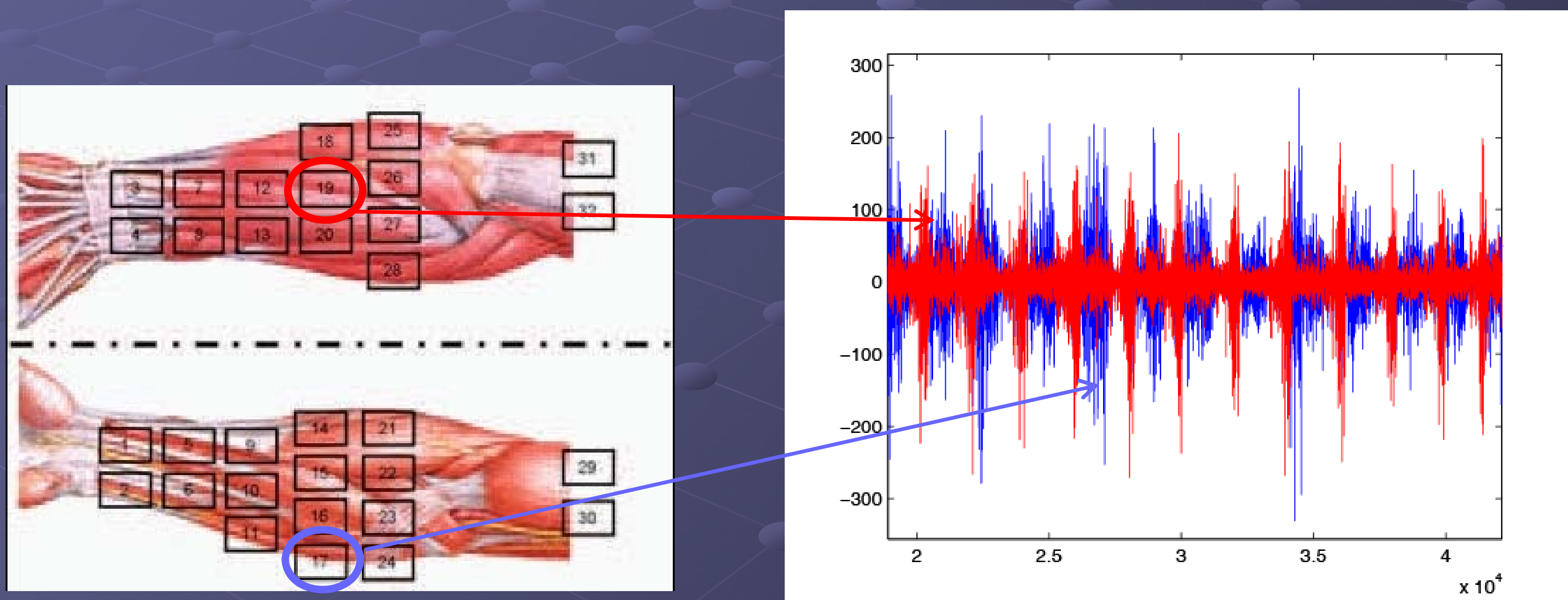
- Non-invasive:
  - Surface EMG

Repetitive movements : Hand opening/closing



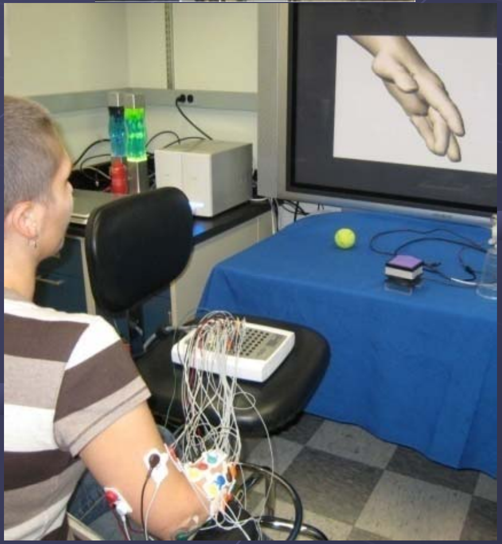


Repetitive movements : Hand rotation (pronation/supination)



Experimental protocol

- Acquisition of non-invasive surface EMG signals from forearm (and upper arm)
- Subjects perform finger and hand movements on cue (audiovisual) – 18 total
- Transradial amputees perform movements also with intact hand simultaneously



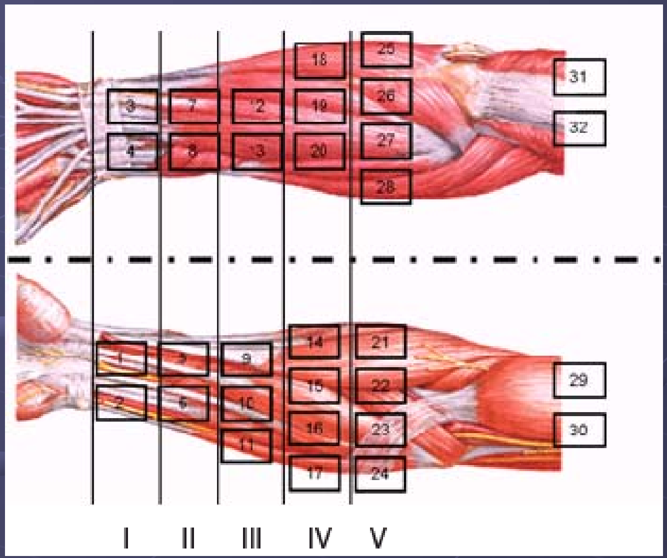
F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, N. V. Thakor, 2007. **Towards the Control of Individual Fingers of a Prosthetic Hand Using Surface EMG Signals**. *Proc EMBC, 2007*.

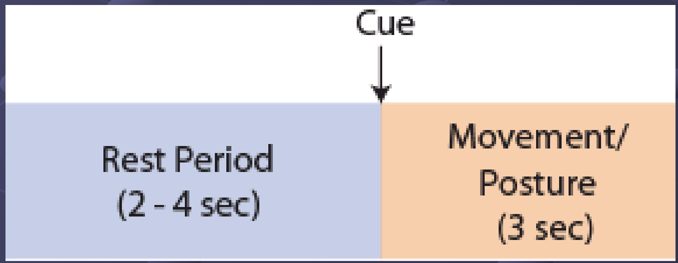
Problem Statement

- Fast pace of development of upper-limb prostheses requires a paradigm shift in EMG-based controls
- Traditional control schemes typically provide *2 degrees of freedom* (DoF):
  - Insufficient for dexterous control of individual fingers
- Surface ElectroMyoGraphy (s-EMG) electrodes placed on the forearm and upper arm of an able bodied subject and a transradial amputee

Experimental protocol (II)

- *Number of electrodes = f(amputation level)* (I-V) ➔ Level I: 32 electrodes, Level V: 12 electrodes
- Single trial duration ~ 6 s
- After movement, subjects are asked to hold position until *rest* cue (~ 3s)

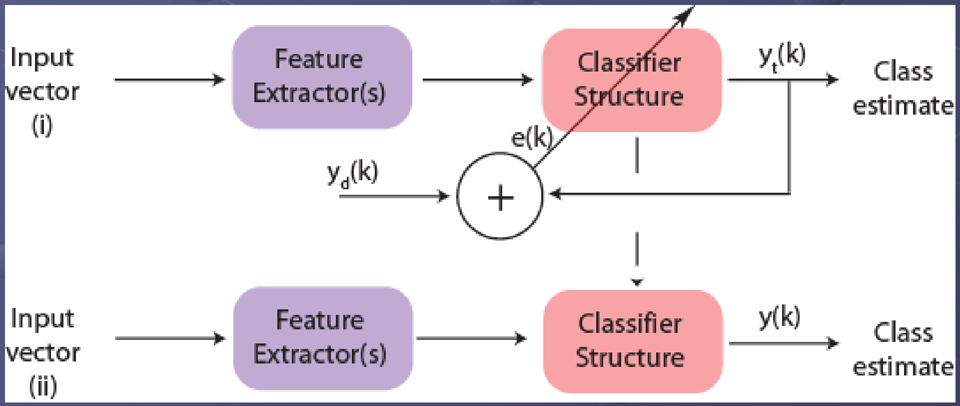


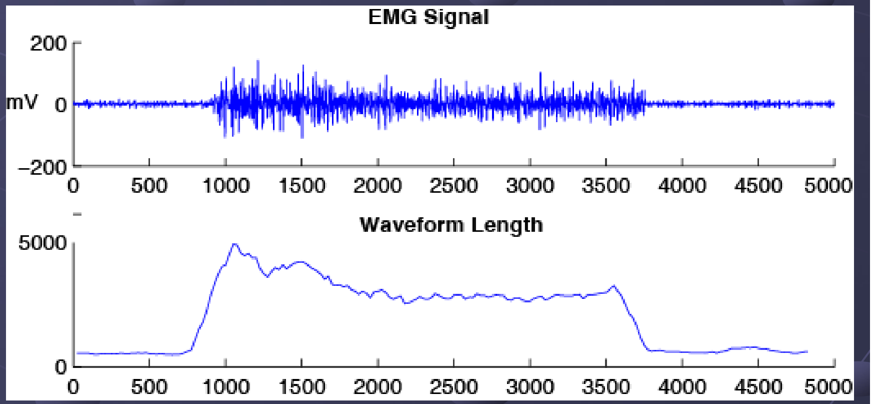


[F. Tenore et al., *Proc EMBC, 2007*.]

Decoding movements

- Extraction of EMG features
- Multilayer neural networks
- Trials divided into: training (~50%), validation (~20%), testing (30%)
    - Selected to take into account potential fatigue





Feature extraction

- "Most crucial part of classification process" [Englehart et al, 1999]
- Only time domain features implemented
  - Real-time classification [Englehart et al, 2003]
- Other possibilities:
  - Time-frequency domain: *histogram*
  - Frequency domain: *cepstral coefficients*
  - Wavelet domain

Implemented Solution (I)

- 12 movements to decode: 5 finger flexion and extension, and combined middle-ring-pinky fingers flexion and extension
- Using the *waveform length* as extracted feature ($l_0 = \sum_{k=1}^{L} |\Delta x_k|$), we train *artificial neural networks* (ANN) to classify the different movements
  - Variable number of input features:12-32
  - ~ 60 hidden layer neurons
  - 12 outputs (→ movements)

Feature extraction: Time domain features (I)

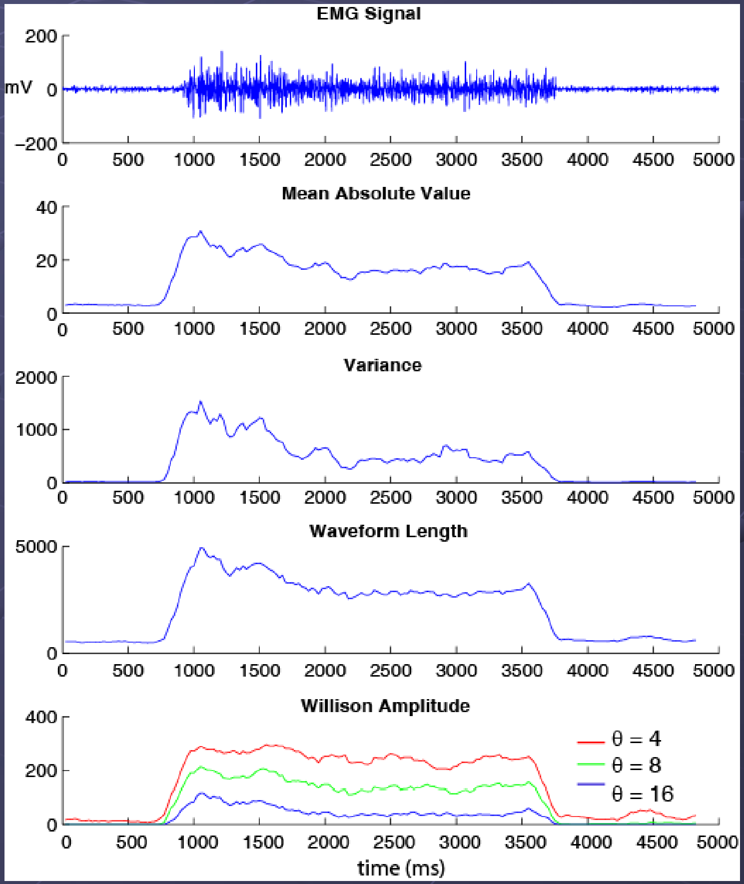
- EMG TD features
  - Exploit characteristics of EMG signals, i.e. presence/density of motor unit action potentials for a given time period
- Characterized by:
  - Extraction of information from data within a time window of brief duration (<300ms)
  - Window is extracted frequently (sliding window: every 25-50 ms) to allow continuity in extracted data

Feature extraction: Time domain features (II)

- Four features examined:
  - Mean absolute value: $\overline{X} = \sum_{i=1}^{N} |x_i|$
  - Variance: $\sigma^2 = \frac{1}{N-1} \sum_{i=1}^{N} |x_i{}^2|$
  - Waveform length: $WL = \sum_{i=1}^{N} |x_i - x_{i-1}|$
  - Willison Amplitude:

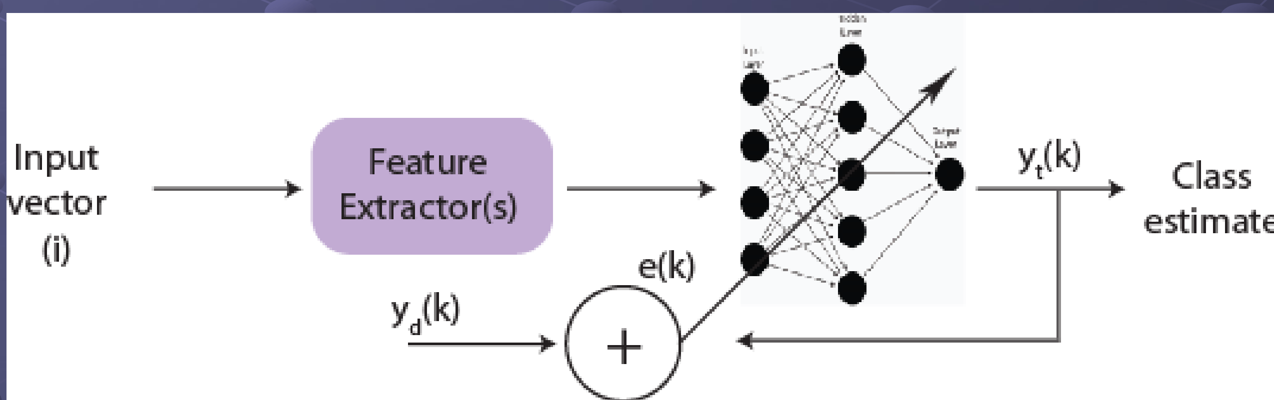
$$W = \sum_{i=1}^{N} f(|x_i - x_{i-1}|)$$

$$f(x) = \begin{cases} 1 & \text{if } x > \theta_0 \\ 0 & \text{otherwise} \end{cases}$$



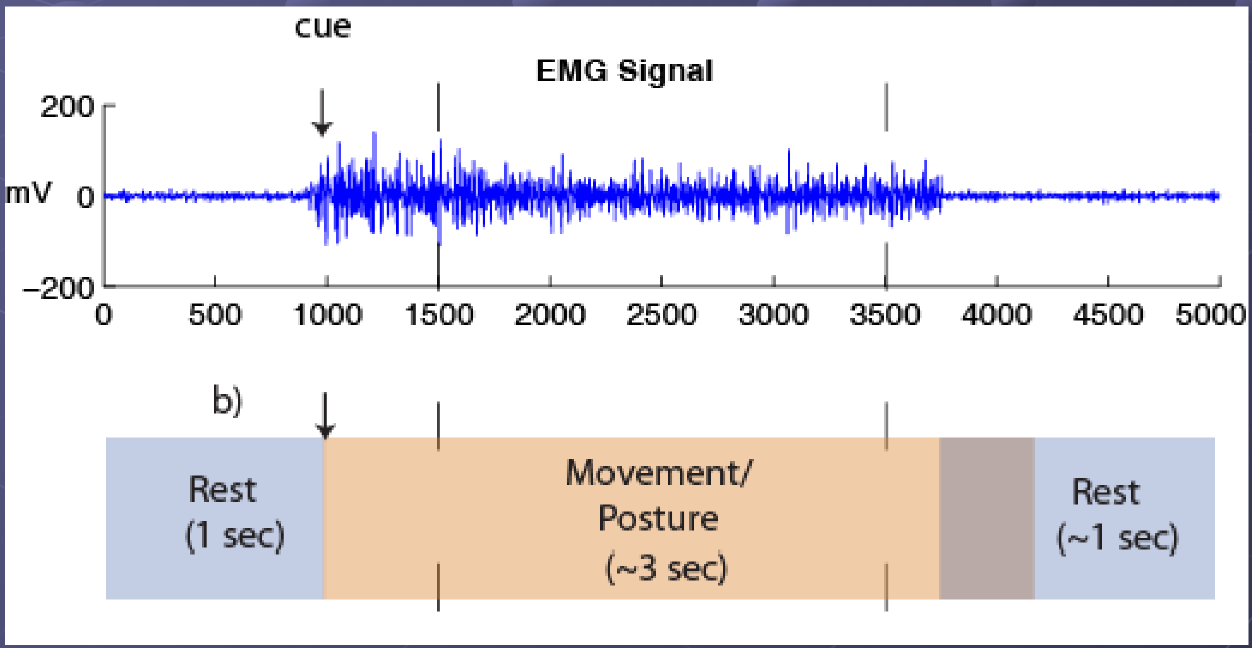
Multilayer Perceptrons

- Multiple layers of computational units: Input, “Hidden”, Output
- Learning through backpropagation ➔ error fed back through network
  - Weights updated through gradient descent optimization



Synchronous classification

- Allows distinction between *n* movement types
- Training/testing occur on contraction (2s duration), where features are stable

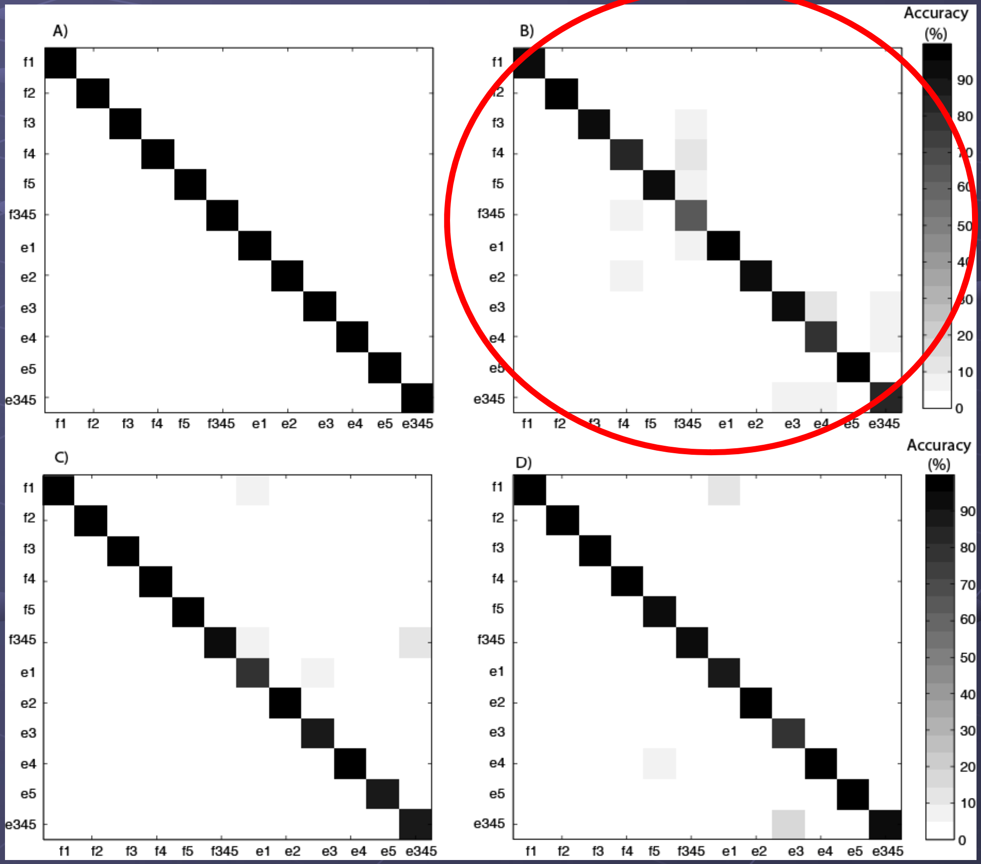


[F. Tenore et al., EMBC 2007]

Results

- 4 subjects, 12 movements
  - 32 electrodes able-bodied subjects,
  - 19 electrodes on transradial amputee
- Confusion matrices: allow identification of misclassified movements
- Transradial amputee is?

Predicted movements



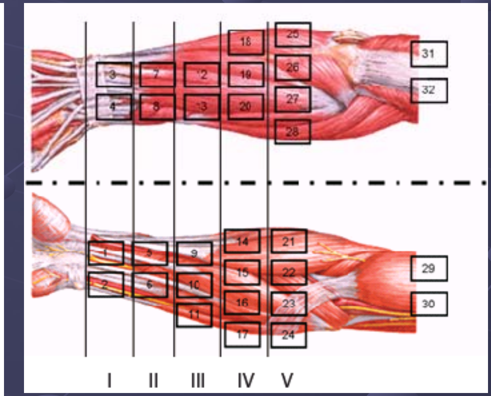
Intended movements

Tenore, F., Ramos, A., Fahmy, A., Acharya, S., Etienne-Cummings, R., and Thakor, N.V. **Decoding of individuated finger movements using surface Electromyography**. Submitted to *IEEE Transactions on Biomedical engineering*

Results (II)

- Waveform length: best feature overall
- Subject A: performed experiment multiple times (>3)
- Subjects B, C: female; A,D: male

Subject	No. elec.	Feat.	Acc.	Subject	No. elec.	Feat.	Acc.
A	32	MAV	98.8±1.1	C	32	MAV	88.8±8.0
		Var	98.8±0.9			Var	87.7±8.0
		WA	98.6±2.5			WA	86.9±9.8
		WL	99.7±0.3			WL	93.6±6.2
	19	MAV	98.3±2.1		19	MAV	84.4±10.9
		Var	98.1±2.3			Var	84.8±11.2
		WA	98.0±2.7			WA	86.9±11.8
		WL	99.1±1.3			WL	92.7±7.6
				D	32	MAV	92.5±6.4
						Var	90.9±8.4
						WA	84.9±4.6
						WL	95.0±6.1
B	19	MAV	82.3±15.7		19	MAV	88.8±9.4
		Var	83.8±13.1			Var	87.8±10.0
		WA	83.3±14.8			WA	80.0±13.0
		WL	87.8±12.3			WL	94.3±5.7



F. Tenore, et al., Submitted to: *IEEE TBME*

Analysis of Results

- Non-parametric tests on the accuracy data (Kruskal-Wallis) show that there IS significant difference between subject A and subjects B, C, D, but *no significant difference* between B, C, D
- Transradial amputee confusion between movements e-f_{345} and e-f_3, e-f_4, e-f_5, but not viceversa

Subject	No. elec.	Feat.	Acc.	Subject	No. elec.	Feat.	Acc.
A	32	MAV	98.8±1.1	C	32	MAV	88.8±8.0
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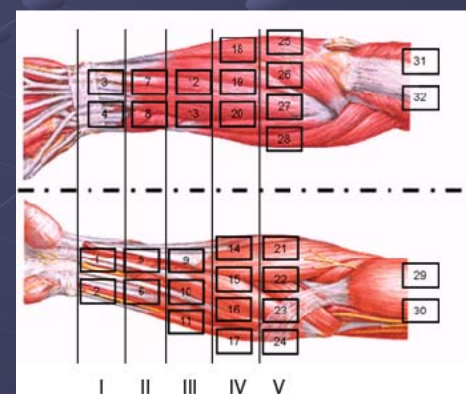


F. Tenore, et al., Submitted to: *IEEE TBME*

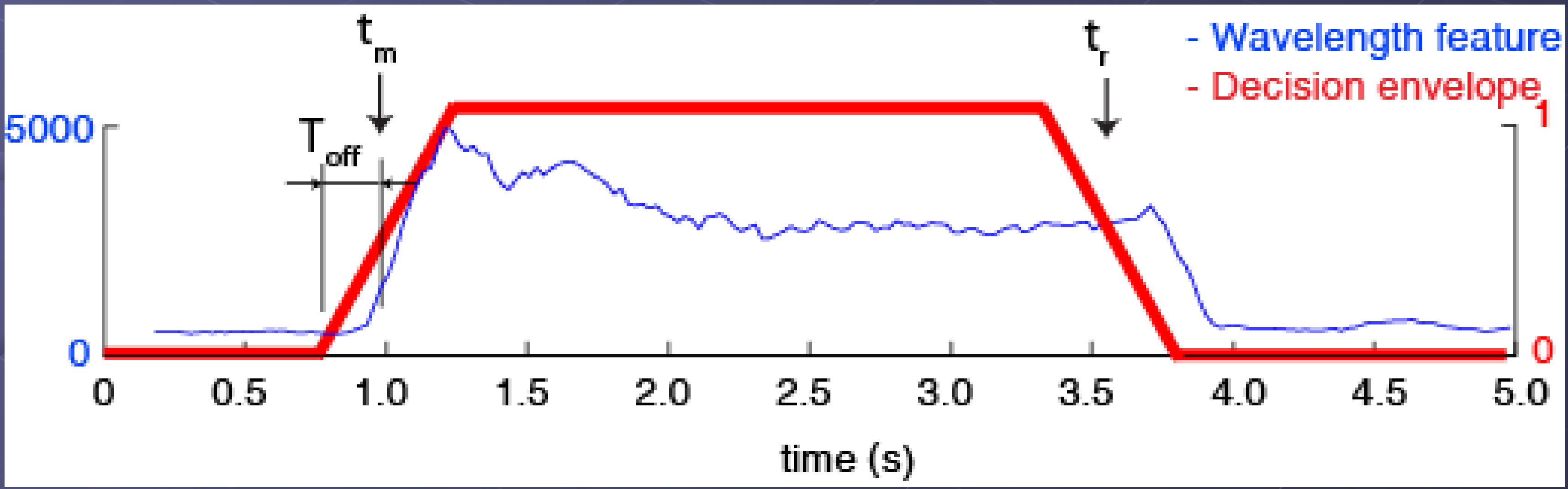
Asynchronous Decoding

- Characterized by *ability to differentiate between rest state and movement states*
- Decoded movement must occur *within 300 ms* of performed movement
- Precise evaluation of states requires direct knowledge of hand/finger position
  ➔ impossible on transradial amputees

Tenore, F., Ramos, A., Fahmy, A., Acharya, S., Etienne-Cummings, R., and Thakor, N.V. Real-time decoding of individuated finger movements using surface Electromyography. Manuscript in preparation

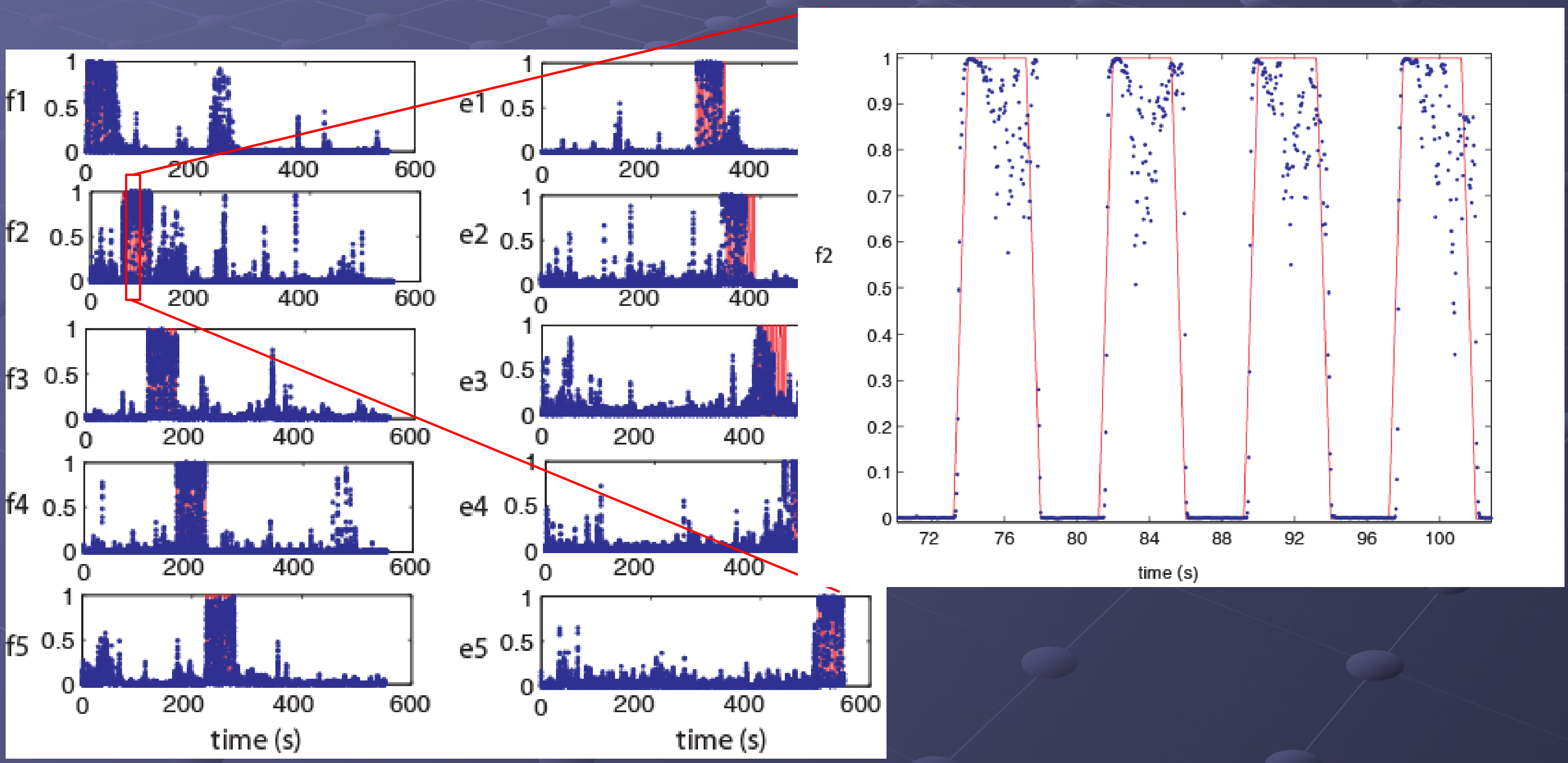
Asynchronous Decoding (II)

- Indirect approach:
  - uses “cue” signal as proxy for finger movement
  - Piecewise linear (fuzzy) decision envelope to weigh output classification



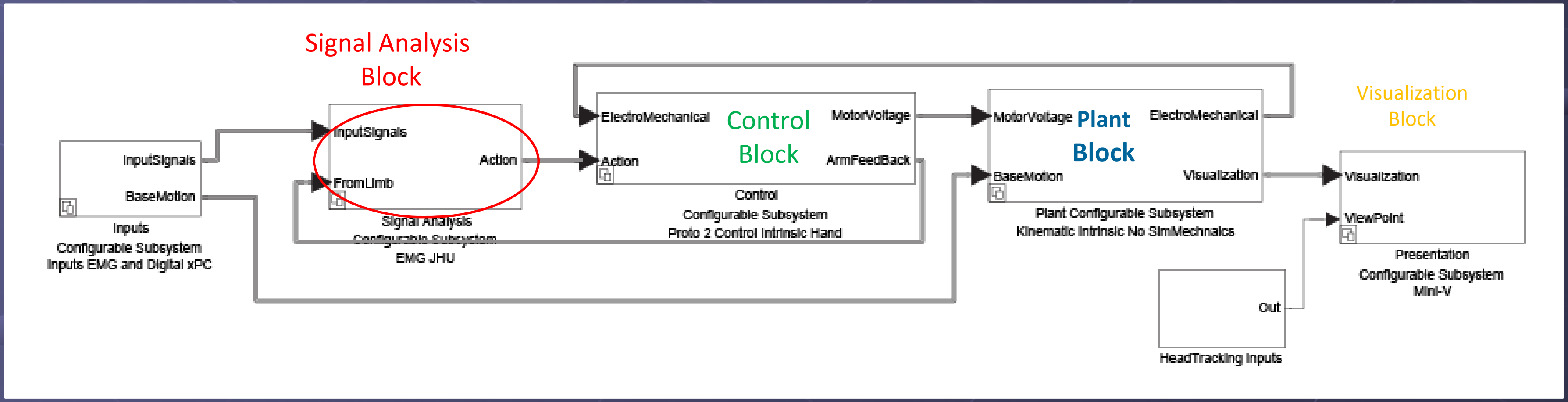
Results

- 10 movements (f_1-f_5, e_1-e_5)



Visualization on Virtual Integration Environment

- VIE provided by JHUAPL for fast prototyping of decoding algorithms
- VIE in action
- Real Time Decoding



Cortical Decoding of Individual Finger Movement

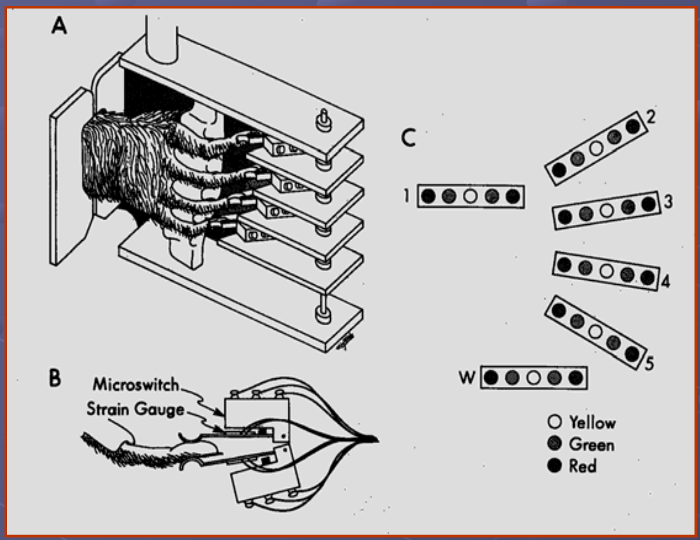
- it is possible to *asynchronously* decode dexterous finger movements where cues indicating the onset movement are not known
- it is possible to decode these movements using spatially-constrained volumes of neurons as typically recorded from a microelectrode array
- decoding accuracy differs due to the configuration or location of arrays within the M1 hand area

Presentation Outline

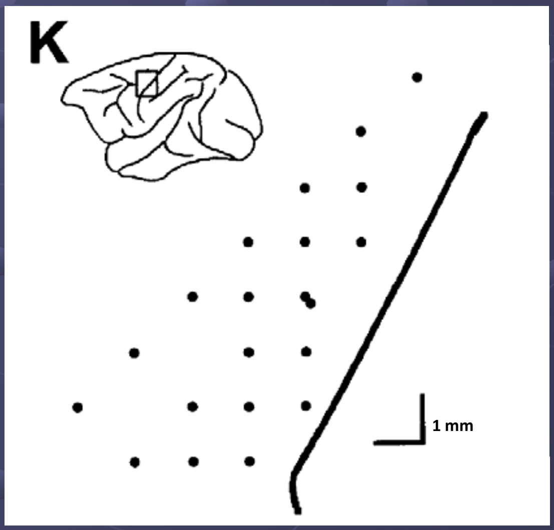
- Introduction
  - Central pattern generators
  - Are CPGs involved in upper limb control?
- Lower Limb Neural Prosthesis
  - Spinal cord injury and locomotion prosthesis
  - Gait controller: *silicon model of spinal cord circuits*
  - Phase controller: *controlling Behavior*
- Upper Limb Neural Prosthesis
  - High degree of freedom prosthetic hands
  - Decoding Arm EMG: *trans-radial prosthesis*
  - Decoding Motor Cortex: *individual finger movements*
- Conclusion and Future
  - Sensory feedback and haptics

Experimental Data

- Three *M. mulatta* trained to perform:
  12 individuated finger movements (f1,f2,…,fw,e1,e2,…,ew)
  6 combined finger movements (f1+2, f2+3, f4+5, e1+2, e2+3, e4+5)



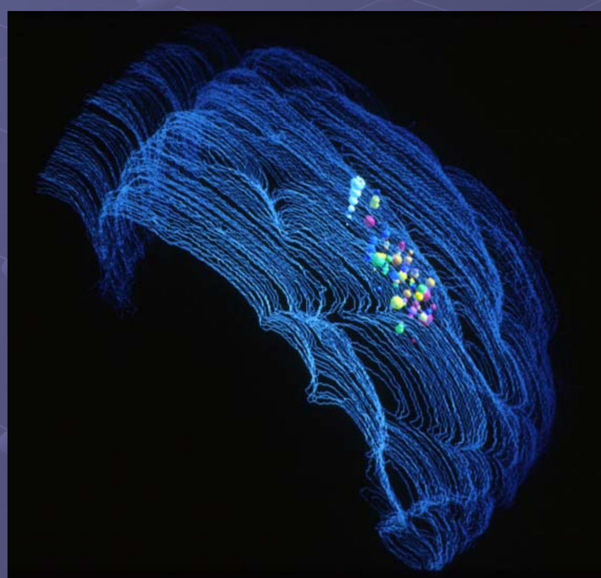
Experimental Setup. A) pistol-grip manipulandum to separate fingers, **B)** bank of LEDs to present visual cues, and **C)** micro-switches to detect finger movement. (Poliakov and Schieber, 1999)

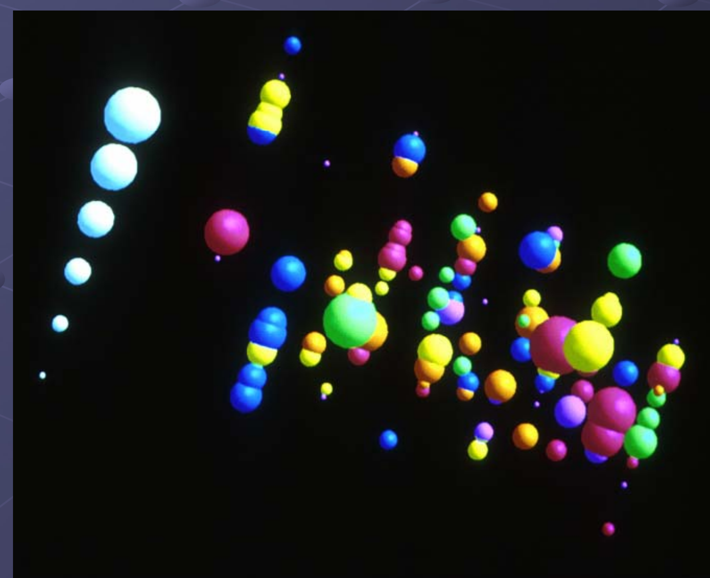


Neuron Recordings. Location of microelectrode penetrations in M1.
325 neurons (monkey C), 125 neurons (monkey G), 115 neurons (monkey K). (Poliakov and Schieber, 1999)

Decoding Challenges

- Fortunately, there are neurons in M1 that code for finger and wrist movements
- Turns out M1 hand region is NOT somatotopically organized
  - neurons are “spatially distributed, intermingled, and physiologically diverse”

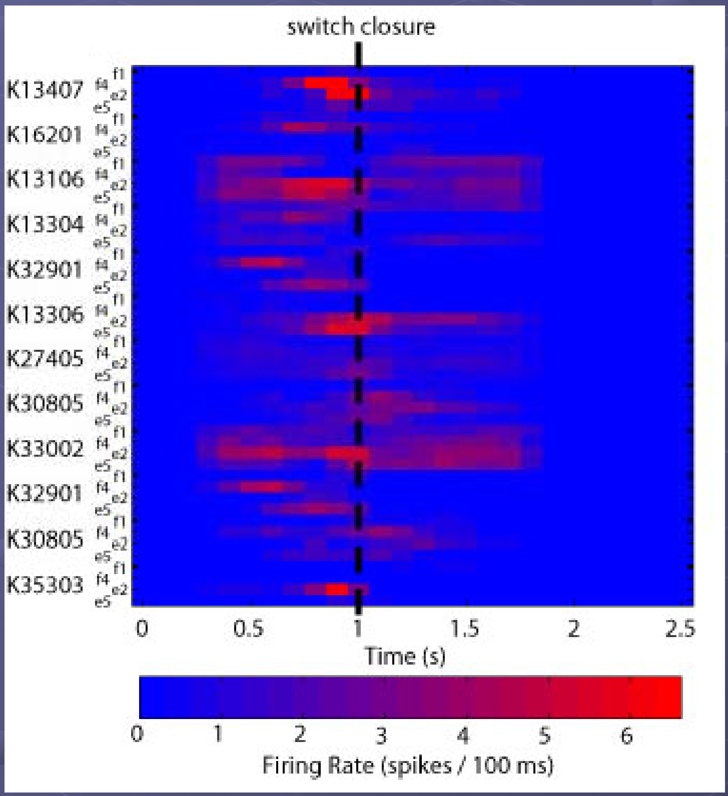


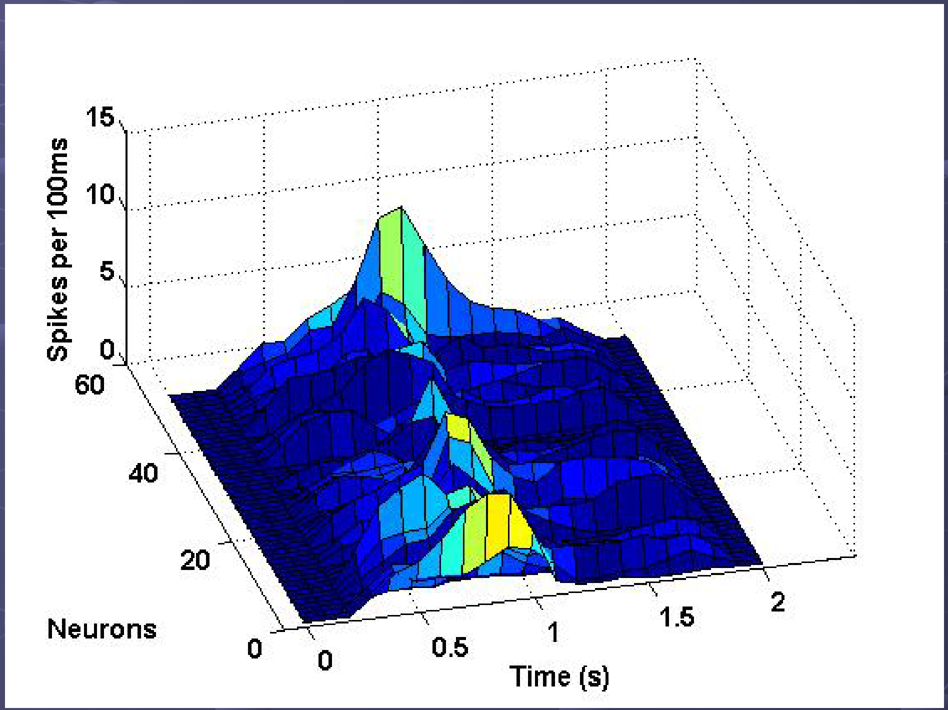


M1 Hand Region. Spheres represent neurons in M1 hand region. Each color is for a different movement type. Size of sphere is proportional to neuron activity for that movement type. (Schieber and Hibbard, 1993)

Input Space Complexity

Top: Temporal evolution of spiking activity from an ensemble of neurons in Monkey K

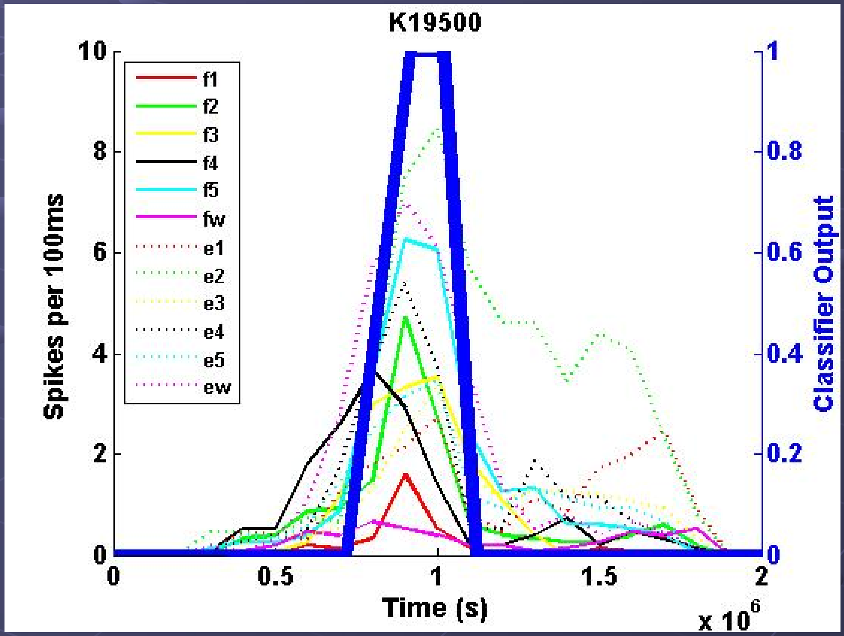




Increased activity around switch closure (1 sec) advocates use of gating classifier to decode movement intent, and dividing input space into hierarchical subspaces.

Gating Classifier

- Train a committee of ANN to distinguish between baseline activity from the onset of movement



- How to train gating classifier?
  - trapezoidal membership function
  - fuzzy output label
  - threshold to produce binary variable

$$g_n(t_k) = \begin{cases} 1 & \text{if } \; P_n\{I(t_k)\} > T_1 \\ 0 & \quad\quad else \end{cases}$$

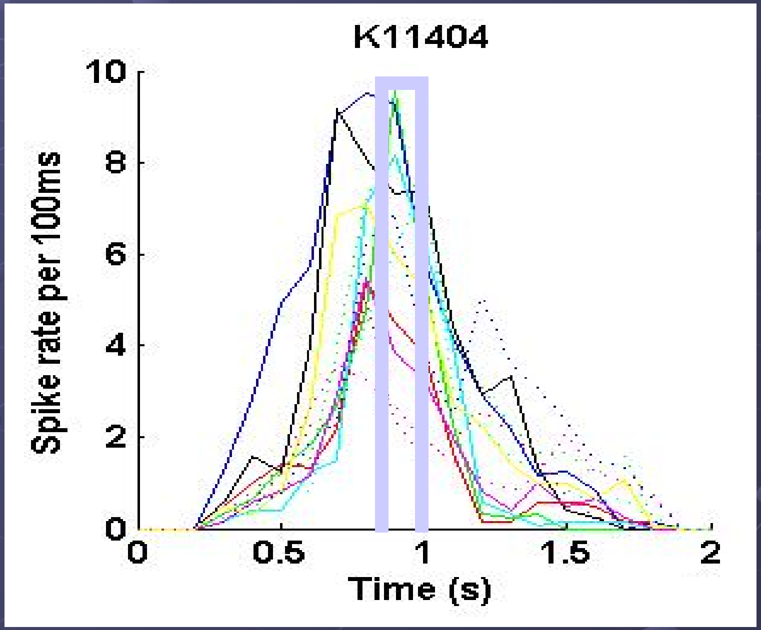
- Majority voting rule chooses committee output of gating classifier

$$G(t_k) = \begin{cases} 1 & \text{if } \; \displaystyle\sum_{t=t_k-t_j}^{t_k} \left(\sum_{n=1}^{N} (g_n(t_k)) > \frac{N}{2} \right) > T_2 \\ 0 & \quad\quad else \end{cases}$$

Movement Classifier

- Train ANN to distinguish amongst each movement type
- How to train movement classifier?
  - assign probability to each movement type during 100 ms before switch closure
  - select movement type with greatest probability

$$s_n(t_k) = \arg\max P_n\{M_i\}$$

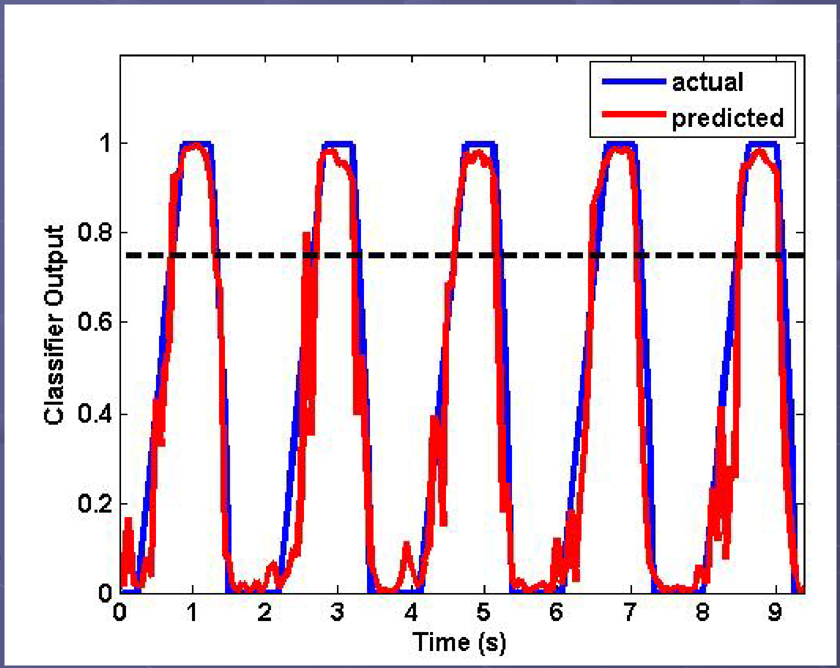


- Majority voting rule chooses committee output of movement classifier

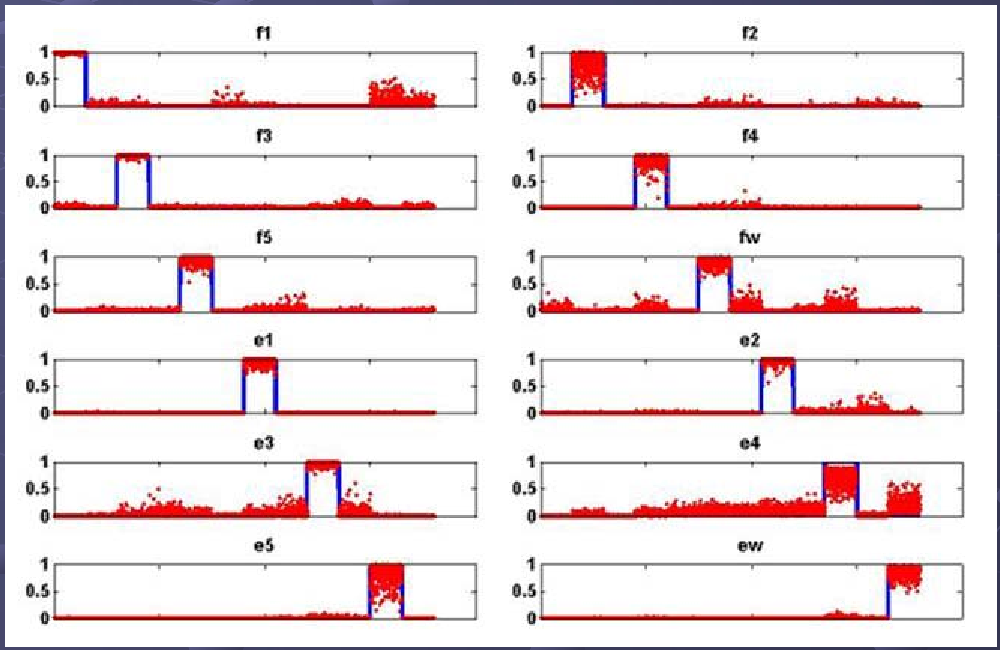
$$S(t_k) = \mathrm{mode}\{s_n(t_k)\}$$

Decoded Output

Gating Classifier



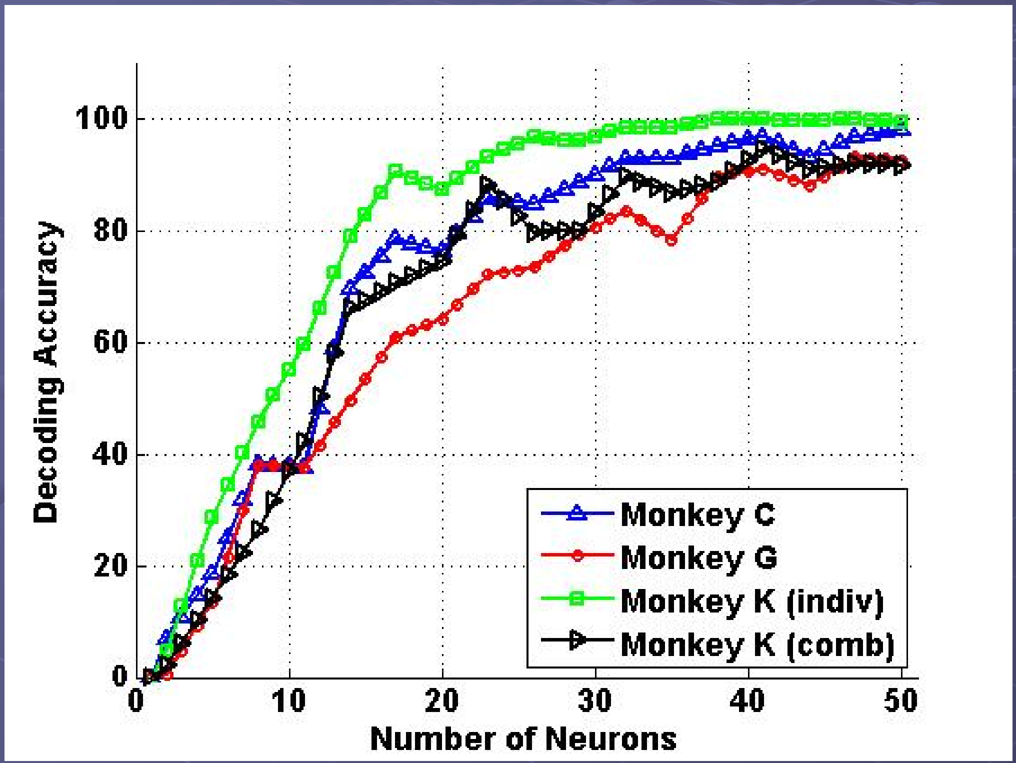
Movement Classifier



- Final decoded output is product of two committee networks

$$F(t_k) = G(t_k) \times S(t_k)$$

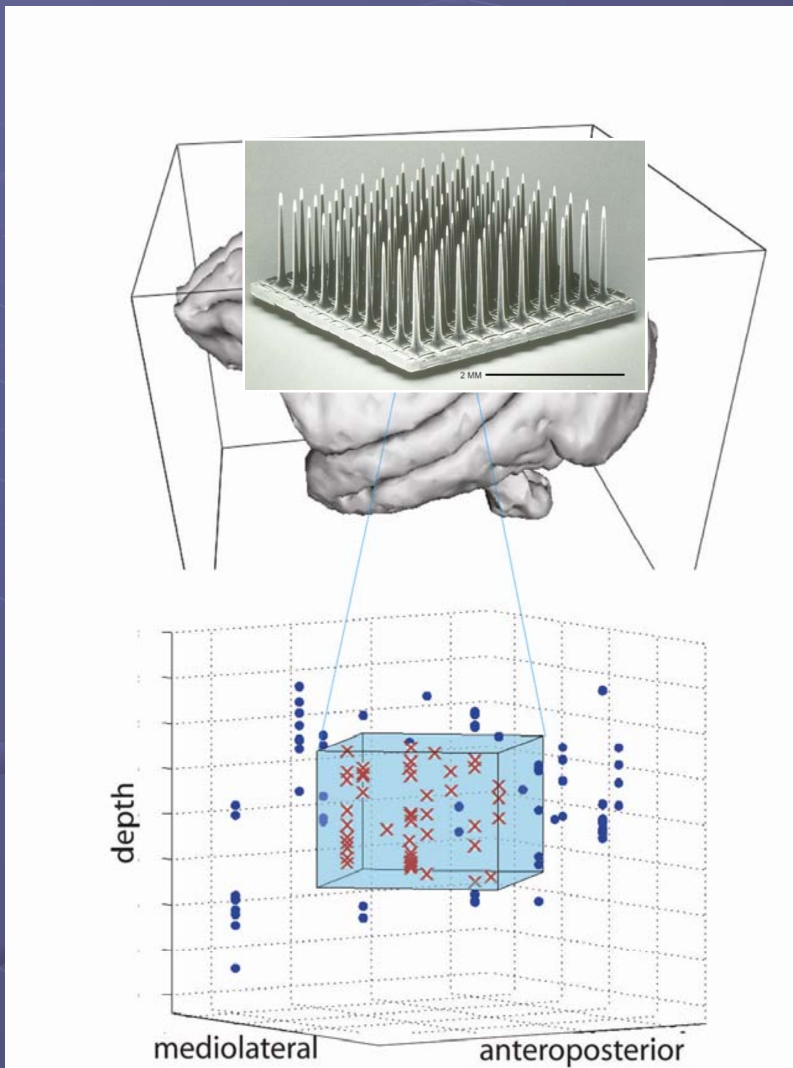
Real-Time Decoding Results



Asynchronous decoding results for individuated and combined finger movements. (Aggarwal et al, submitted, 2007)

- For individuated movements, decoding accuracy was as high as 99.8% for monkey K using 40 neurons, and 95.4% using only 25 neurons
- Although lower, decoding accuracy was still 96.2% for monkey C and 90.5% for monkey G using 40 neurons
- When combined movements were included, average decoding accuracy was 92.5% for all 18 movement types using 40 neurons for monkey K

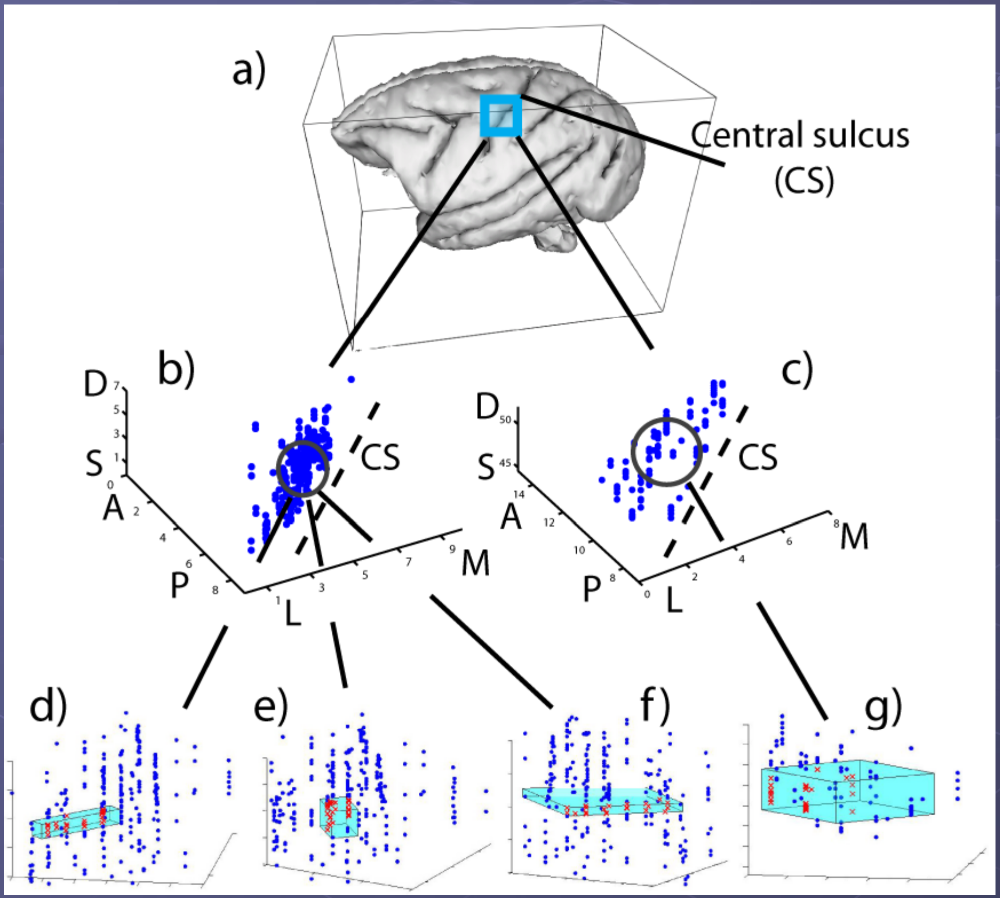
Virtual Electrode Arrays



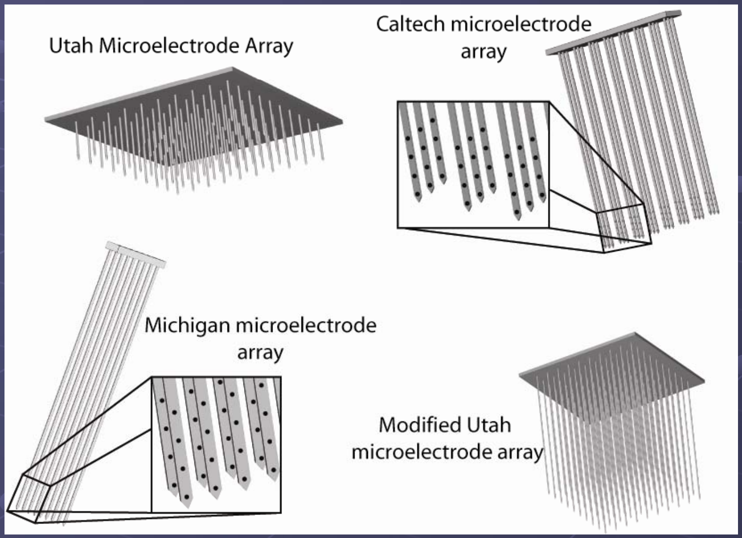
Primary motor cortex hand area where neurons were recorded from.

One possible voxel where electrode array could be placed. Blue dots represent each neuron recorded from (115 neurons). Red crosses represent neurons enclosed within given voxel (48 neurons).

Virtual Electrode Arrays

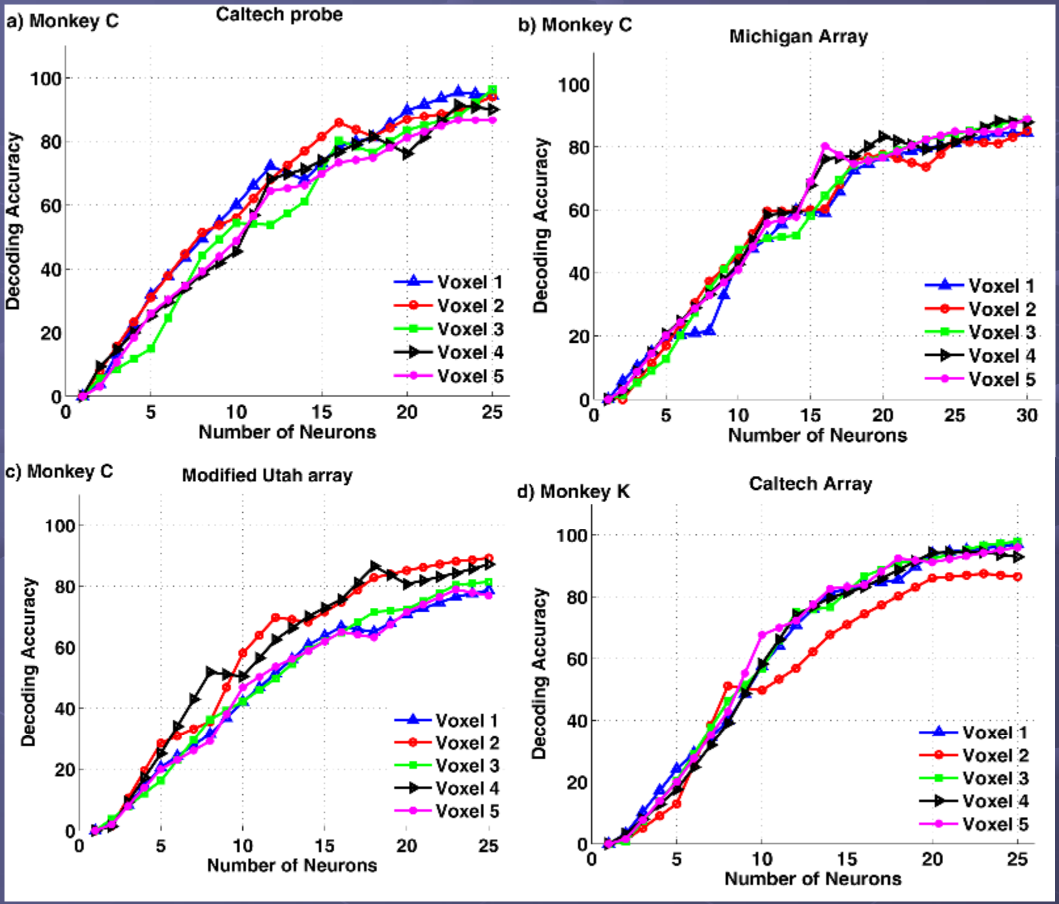


Approximate recording footprints from four different electrode array configurations (Acharya et al, IEEE TNSRE,2008)



- Each voxel configuration, corresponding to different arrays, were placed at five distinct locations within the recording space.

Real-Time Decoding Results



Asynchronous decoding results for different voxel configurations (Acharya et al, IEEE TNSRE,2008)

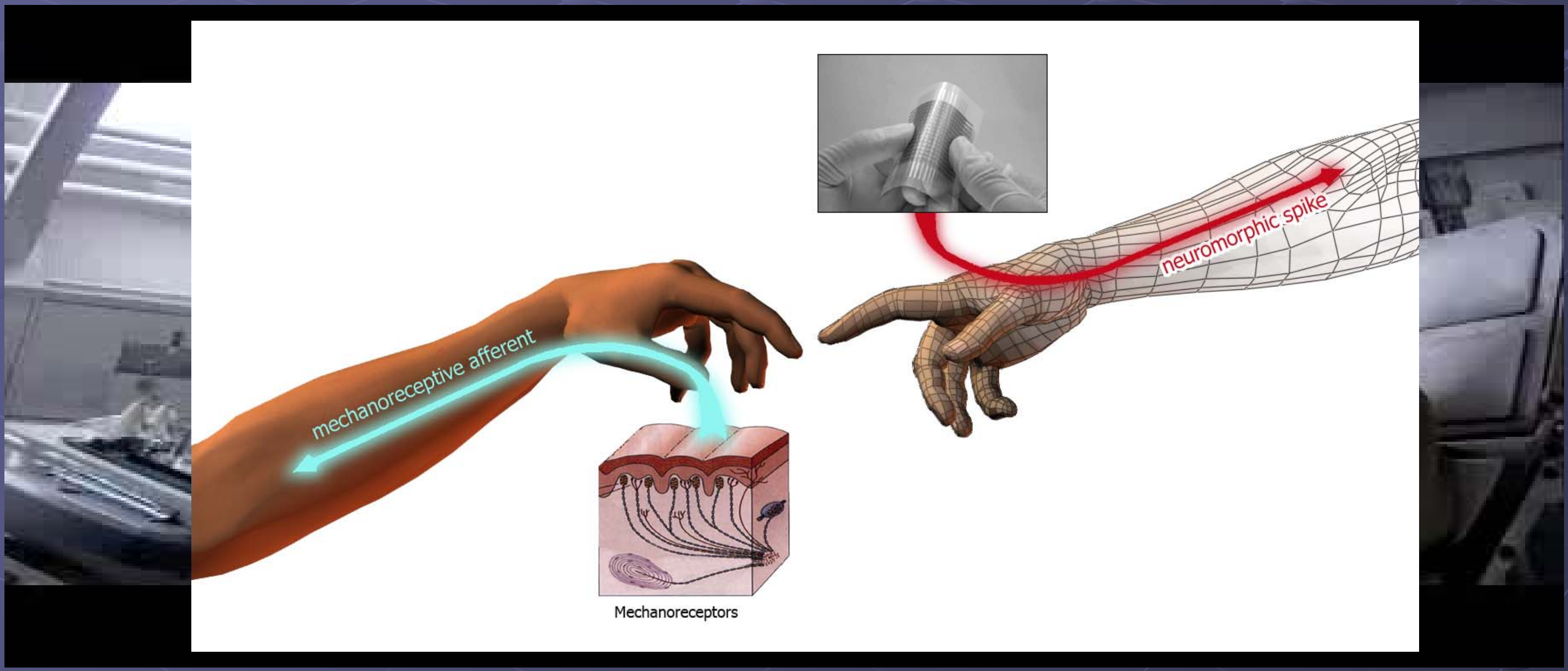
- Average decoding accuracy was >80% with as few as 25 neurons in monkey C and >85% with as few as 20 neurons in monkey K, irrespective of voxel configuration and placement
- For the majority of cases, no significant differences ($p<0.01$) were detected in the overall decoding accuracies due to voxel placements.

Playing the Cortical Piano

Presentation Outline

- Introduction
  - Central pattern generators
  - Lower Limb and Upper Limb CPGs (?)
- Lower Limb Neural Prosthesis
  - Spinal cord injury and Spinal Prosthesis
  - Gait controller: *Silicon model of spinal cord circuits*
  - Phase controller: *Controlling Behavior*
- Upper Limb Neural Prosthesis
  - High degree of freedom prosthetic hands
  - Decoding Arm EMG: *Trans-radial prosthesis*
  - Decoding Motor Cortex: *Individual Finger Movements*
- Conclusion and Future
  - Sensory Feedback and Haptics

Conclusions and Future



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Questions?