Towards Neurally Integrated High Degrees of Freedom Prosthetic Limbs

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

Source: Mellen et al., 1995; Grillner & Zangger, 1984; Minassian et al., 2004
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CPGs for arm movements

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

[Image: www.colszoo.org/animalareas/aforest/gorilla.html]
CPGs for arm movements

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

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”

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

2. Activate CPG
   + tonic stimulation initiates locomotion
     - epidural spinal cord stimulation (ESCS)
     - intraspinal microstimulation (ISMS)

3. Generate “Efferent Copy”
   + monitor sensorimotor state
     - external sensors on limbs
     - internal afferent recordings

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

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

- Seeks to emulate (specific) biological systems in both structure and function.
- Is based on the fact that the powerful organizing principles found in the nervous system can be realized in silicon integrated circuits.

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

Source: Ekeberg and Pearson, J Neurophys, 2005
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.]

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

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

Source: Vogelstein et al., IEEE TBioCAS, (submitted)
Results: SiCPG Chip Controls Locomotion in a Paralyzed Cat

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

<table>
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<th>$\Phi$</th>
<th>Predicted BLi</th>
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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)

Neuroprosthetic control via external stimulation (average effects)

Conclusion: locomotion controller can functionally replicate output of natural neural control system through phasic spinal cord stimulation
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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
Source: the 20th Century Fox
Thanks to: Kyle Fritz

(same source)
State-of-the-art of Prosthetic Hands

JHU/APL RP2009 Prototype II Hand
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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
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

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** = \( f(\text{amputation level}) \) (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, 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:**
  \[ X = \frac{1}{N} \sum_{i=1}^{N} |x_i| \]

- **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?

Results (II)

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

<table>
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<th>Subject</th>
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<th>Accuracy</th>
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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$_3$, e-f$_4$, e-f$_5$, but not vice versa.

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<td>94.3±5.7</td>
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</table>

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

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 (f₁-f₅, e₁-e₅)
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
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, ..., f6, e1, e2, ..., e6)
- 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

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

Majority voting rule chooses committee output of gating classifier

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

\[ S(t_k) = \text{mode}\{s_n(t_k)\} \]
Decoded Output

Final decoded output is product of two committee networks

\[ F(t_k) = G(t_k) \times S(t_k) \]
Real-Time Decoding Results

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.

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

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.

Asynchronous decoding results for different voxel configurations (Acharya et al, IEEE TNSRE, 2008)
Playing the Cortical Piano
Presentation Outline

Introduction
- Central pattern generators
- Lower Limb and Upper Limb CPGs (?)

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Conclusions and Future
Acknowledgements

ONR Award #N00014-00-1-0562
ONR Award #N00014-99-1-0984
NIH Neuroengineering Training Grant
NSF Graduate Research Fellowship
DARPA Revolutionizing Prosthetics
Telluride Neuromorphic Engineering Workshop
NSF ERC CISST at JHU
Questions?