Silicon and Biological Adaptive Neural Circuits

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“in silico” neural systems design

Neural Systems

Learning & Adaptation

VLSI Microchips
Today’s Hottest Microchip

Intel’s Itanium 2

The numbers …

– 0.5 billion transistors in 120nm CMOS
– 1.6GHz clock, 64-bit instruction, 9MB L3 cache, 6.4GB/s I/O
– 2553 SPECfp_base2000 (30% faster than 2.8GHz P4)
– 130 Watts

… and what they mean

Faster/cooler:

• Scientific computing
• Database search
• Web surfing
• Video games

What about intelligence?

Source: IEEE ISSCC’2002
Chips and Brains

• **Itanium:**
  - $3 \times 10^9$ floating op/s
    - $5 \times 10^8$ transistors
    - $2 \times 10^9$ Hz clock
  - $10^{10}$ Hz memory I/O
    - 128-b data bus @ 400MHz
  - 130 Watts

• **Human brain:**
  - $10^{15}$ synaptic op/s
    - $10^{15}$ synapses
    - 1 Hz average firing rate
  - $10^{10}$ Hz sensory/motor I/O
    - $10^8$ nerve fibers
  - 25 Watts

• Silicon technology is approaching the raw computational power and bandwidth of the human brain.

• However, to emulate brain intelligence with chips requires a radical paradigm shift in computation:
  - Distributed representation in massively parallel architecture
    - *Local adaptation and memory*
    - *Sensor and motor interfaces*
  - Physical foundations of computing
Voltage-dependent *n*-channel

- *Electron* transport between source and drain
- Gate controls energy barrier for electrons across the channel
- Boltzmann distribution of *electron energy* produces exponential *increase* in channel conductance with gate voltage

Cross-section of *nMOS* transistor in 0.18µm CMOS process (Intel, 2002)
**Voltage-dependent p-channel**

- *Hole* transport between source and drain
- Gate controls energy barrier for holes across the channel
- Boltzmann distribution of *hole energy* produces exponential *decrease* in channel conductance with gate voltage
Physics of Neural Computation

Silicon and Lipid Membranes

Mead, 1989

Voltage-dependent $p$-channel

- Hole transport between source and drain
- Gate controls energy barrier for holes across the channel
- Boltzmann distribution of hole energy produces exponential decrease in channel conductance with gate voltage

Voltage-dependent conductance

- $K^+/Na^+$ transport across lipid bilayer
- Membrane voltage controls energy barrier for opening of ion-selective channels
- Boltzmann distribution of channel energy produces exponential increase in $K^+/Na^+$ conductance with membrane voltage
Physics of Neural Computation

Silicon and Biochemical Synapses

Mead 1989

Voltage-dependent $p$-channel

- *Hole* transport between source and drain
- Gate controls energy barrier for holes across the channel
- Boltzmann distribution of *hole energy* produces exponential *decrease* in channel conductance with gate voltage

Voltage-dependent quantal release

- $K^+/Na^+$ through postsynaptic membrane
- Presynaptic membrane voltage controls energy barrier for neurotransmitter release
- Boltzmann distribution in *quantal release energy* produces exponential dependence of postsynaptic $K^+/Na^+$ conductance
Why Develop “Neural” Silicon Chips?

Biology Motives:
- *In silico* emulation of neural and sensory-motor systems
  - *Real-time computational power*
  - *Accounts for noise and imprecision in neural elements*
- Analysis by synthesis
  - *Emulating form and structure of neural systems provides better understanding, accounting for physical and architectural constraints*
- Interfacing silicon with neurons and synapses *in vivo*
  - *Allows to observe and control neural and synaptic activity*

Engineering Motives:
- Efficiency of implementation
  - *Lower power, smaller size*
- Real-world interface
  - *Integrated sensors and actuators*
  - *Analog, continuous-time dynamics*
  - *Intelligent brain-machine interfaces!*
Neuromorphic Systems Design Flow

Neural Model

Chip Layout

Circuit Design and Simulation

Microfabrication

Microchip(s)

Chip Testing

System Integration

Neuromorphic System

http://www.mosis.org
Silicon Model of Visual Cortical Processing

Neural model of boundary contour representation in V1, one orientation shown (Grossberg, Mingolla, and Williamson, 1997)

Single-chip focal-plane implementation (Cauwenberghs and Waskiewicz, 1999)
**NeuroDyn: Biophysical Neurodynamics in Analog VLSI**

Yu and Cauwenberghs 2009

The NeuroDyn Board consists of 4 neurons fully connected through 12 synapses. All parameters are individually programmable and have biophysically-based parameters governing the conductances, reversal potentials, and voltage-dependance of the channel kinetics.

**Programmable Parameters: 384 total**

### Neurons $V_i$

- $\alpha_{ni}(V)$
- $\beta_{ni}(V)$
- $\frac{m_i}{n_i}$
- $\frac{h_i}{h_i}$
- 4x3x7*

### Synapses $s_{ij}$

- $\alpha_{rij}(V_{pre})$
- $\beta_{rij}(V_{post})$
- $g_{syn_{ij}}$
- $E_{syn_{ij}}$
- 12x7*

*All rates $\alpha$, $\beta$ are 7-point sigmoidal spline regression functions.*

$\alpha_{(V_k)}$, $\beta_{(V_k)}$, $k = 1,...,7$

The NeuroDyn Board consists of 4 neurons fully connected through 12 synapses. All parameters are individually programmable and have biophysically-based parameters governing the conductances, reversal potentials, and voltage-dependance of the channel kinetics.
The NeuroDyn chip emulates detailed neural and synaptic dynamics in silicon by implementing rate-based models of voltage-gated and ligand-gated channel kinetics.
**NeuroDyn** Synaptic Coupling

Uncoupled

Mutual inhibitory synaptic coupling
Generalized Map-Based Neural Dynamics
Izhikevich 2003; Rulkov, Timofeev & Bazhenov 2004; Mihalas & Niebur 2009

\[ v' = 0.04v^2 + 5v + 140 - u + I \]
\[ u' = a(bv - u) \]

if \( v = 30 \text{ mV} \), then \( v \leftarrow c, \ u \leftarrow u + d \)

Regular spiking (RS)

Intrinsically bursting (IB)

Chattering (CH)

Fast spiking (FS)

Thalamo-cortical (TC)

Resonator (RZ)

Low-threshold spiking (LTS)

Electronic version of the figure and reproduction permissions are freely available at www.izhikevich.com
Generalized HH/ML Neural Dynamics
Yu, Sejnowski, and Cauwenberghs 2010

(a) Hodgkin Huxley

(b) Morris Lecar

(c) Extended Morris Lecar
NeuroDyn Tonic Spiking

Matlab digital simulation

NeuroDyn analog emulation

Yu, Sejnowski, and Cauwenberghs 2011
**NeuroDyn** Phasic Spiking

*Matlab* digital simulation

(a) $n, m, h$ vs. $V_m$ (mV)

(b) $\tau$ (ms) vs. $V_m$ (mV)

*NeuroDyn* analog emulation

(c) $n, m, h$ vs. $V_m$ (mV)

(d) $\tau$ (ms) vs. $V_m$ (mV)

(e) $V_m$ vs. Time (ms)

(f) $I_{ext}$, $V_m$, $m$, $h$, $n$ vs. Time (ms)

Yu, Sejnowski, and Cauwenberghs 2011
NeuroDyn Tonic Bursting

Matlab digital simulation

(a) $w, m_{ss}, h$ vs $V_m$ (mV)
(b) $\tau$ (ms)

NeuroDyn analog emulation

(c) $w, m_{ss}, h$ vs $V_m$ (mV)
(d) $\tau$ (ms)

(e) $V_m$ vs $t$,
$w, m_{ss}, h$ vs $t$,
$I_{ext}$ vs $t$

(f) $V_m$, $m_{ss}$, $h$, $w$ vs $t$

Yu, Sejnowski, and Cauwenberghs 2011
Change Threshold Detection APS CMOS Imager

Chi, Mallik, Clapp, Choi, Cauwenberghs and Etienne-Cummings (2007)

- Event-driven video compression
  - Change detection and threshold encoding on the focal plane
- 6T pixel combines APS and change event coding
- 4.3mW power at 3V and 30fps
Change Detection APS: Compression and Reconstruction

Frame 0

Frame 50

Uncompressed

Low Threshold

High Threshold

Change Events

Reconstructed
Event-Coding Silicon Retina
Zaghloul and Boahen, 2006

- Models coding and communication of visual events in the mammalian retina and optic nerve
  - Integrated photosensors (rods)
  - On and off transient and sustained ganglia cell outputs
    - Spatiotemporal compressed coding and communication in optic nerve
    - Address-event coding of spikes
Reconfigurable Synaptic Connectivity and Plasticity

From Microchips to Large-Scale Neural Systems
Address-Event Representation (AER)

Lazzaro et al., 1993; Mahowald, 1994; Deiss 1994; Boahen 2000

- AER emulates extensive connectivity between neurons by communicating spiking events time-multiplexed on a shared data bus.
- Spikes are represented by two values:
  - Cell location (address)
  - Event time (implicit)
- All events within $\Delta t$ are “simultaneous”
Address-Event Synaptic Connectivity
Goldberg, Cauwenberghs and Andreou, 2000

- ‘Virtual’ synapses
  - Dynamically reconfigurable
  - Wide-ranging connectivity
  - Rewiring and synaptic plasticity
- Quantal release: \( R = n \, p \, q \)
  - \( n \): multiplicity (repeat event)
  - \( p \): probability of release (toss a coin)
  - \( q \): quantity released (set amplitude)
Silicon Membrane Array Transceiver
Vogelstein, Mallik and Cauwenberghs, 2004

- Voltage-controlled membrane ion conductance
  - Event-driven activation
  - Dynamically reconfigurable:
    - conductance $g$
    - driving potential $E$

- Address-event encoding of pre-and post-synaptic action potentials
Silicon Membrane Circuit

$g_i(t)$ ion-specific membrane conductance

$E_i$ ion-specific driving potential

Synapse subcircuit

Action potential generation and AER handshaking
Reconfigurable Silicon Large-Scale Neural Emulator

Vogelstein, Mallik and Cauwenberghs, 2007

- **9,600 neurons**
  - 4 silicon membrane chips (IFAT)
- **4 million, 8-bit “virtual” synapses**
  - 128MB (32bX4M) non-volatile **RAM**
- **1 million synaptic updates per second**
  - 200MHz Spartan II Xilinx FPGA “**MCU**”
- **Dynamically reconfigurable**
  - Rewiring and synaptic plasticity (STDP etc.)
  - Driving potential (**DAC**) and conductance (**IFAT**)
Hierarchical Vision and Saliency-Based Acuity Modulation

Vogelstein, Mallik, Culurciello, Cauwenberghs, and Etienne-Cummings, NECO 2007

- IFAT Cortical Model
  - 4800 silicon neurons
  - 4,194,304 synapses

- Octopus Silicon Retina
  - 80 x 60 pixels
  - AER spiking output

- OR image
- Simple cell response
- Saliency map
Spike Timing-Dependent Plasticity

Bi and Poo, 1998
Spike Timing-Dependent Plasticity
in the Address Domain
Spike Timing-Dependent Plasticity on the IFAT

Vogelstein et al, NIPS*2002
Achieving (or surpassing) human-level machine intelligence will require a convergence between:

• Advances in computing resources approaching connectivity and energy efficiency levels of computing and communication in the brain;
• Advances in training methods, and supporting data, to adaptively reduce algorithmic complexity.
Example: Board Games (Chess and Go)

- Complexity of typical strategic board games precludes exact solution through complete tree search for all but the simplest games (smallest boards).
  - *Chess and Go are EXPTIME-complete: perfect strategy requires search time exponential in board size.*
- Humans handle game complexity by pattern recognition and sequence recall, rather than tree search, acquired through extensive experience.
  - *Novices routinely defeat computer Go, which fails to “see” the board like humans.*
  - *The need to “see” board patterns calls for adaptive neuromorphic approaches.*

### Machine Complexity

- Throughput; Memory; Power; Size

### Game Complexity

- Game tree depth * breadth

<table>
<thead>
<tr>
<th></th>
<th>Throughput</th>
<th>Memory</th>
<th>Power</th>
<th>Size</th>
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<tbody>
<tr>
<td>Digital computer</td>
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<tr>
<td>Humanoid computer</td>
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<tr>
<td>Human brain</td>
<td>$10^{15}$ synOP/s; 15W</td>
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- Deep Blue/Deep Fritz
- Kasparov
  - ELO ≈ 2,800 (world champion)
- Chess
  - (8x8)
  - 10^{123}
- Go
  - (19x19)
  - 10^{360}

The game of Go (19x19 version)
Scaling and Complexity Challenges

- Scaling the event-based neural systems to performance and efficiency approaching that of the human brain will require:
  - Scalable advances in silicon integration and architecture
    - Scalable, locally dense and globally sparse interconnectivity
      - Hierarchical address-event routing
    - High density (10^{12} neurons, 10^{15} synapses within 5L volume)
      - Silicon nanotechnology and 3-D integration
    - High energy efficiency (10^{15} synOPS/s at 15W power)
      - Adiabatic switching in event routing and synaptic drivers
  - Scalable models of neural computation and synaptic plasticity
    - Convergence between cognitive and neuroscience modeling
    - Modular, neuromorphic design methodology
    - Data-rich, environment driven evolution of machine complexity
3-D Integrated Silicon Neuromorphic Processor

Park, Joshi, Yu, Maier, and Cauwenberghs, 2010

- 65,000, two-compartment neurons
  - Conductance-based integrate and fire array transceiver (IFAT)
- 65 million, 32-bit “virtual” synapses
  - Conductance-based dynamical synapses
  - Dynamic table-look in embedded memory (2Gb DRAM)
- Locally dense, globally sparse synaptic interconnectivity
  - Hierarchical address-event routing (HiAER)
  - Dynamically reconfigurable
  - Asynchronous spike event I/O interface
Phase Change Memory (PCM) Nanotechnology

Intel/STmicroelectronics (Numonyx) 256Mb multi-level phase-change memory (PCM) [Bedeschi et al, 2008]. Die size is 36mm² in 90nm CMOS/Ge2Sb2Te5, and cell size is 0.097 µm².

(a) Basic storage element schematic, (b) active region of cell showing crystalline and amorphous GST, (c) SEM photograph of array along the wordline direction after GST etch, (d) I-V characteristic of storage element, in set and reset states, (e) programming characteristic, (f) I-V characteristic of pnp bipolar selector.

- Scalable to high density and energy efficiency
  - < 100nm cell size in 32nm CMOS
  - < pJ energy per synapse operation
Large-Scale Mixed-Signal Sensory Computation

• **Massive Parallelism**
  - distributed representation
  - local memory and adaptation
  - analog sensory interface
  - physical computation
  - analog accumulation on single wire

• **Inherently Scalable**
  silicon area and power scale linearly with throughput

• **Highly Efficient**
  factor 100 to 10,000 less energy/operation than DSP

• **Limited Precision**
  - analog mismatch and nonlinearity (WYDINWYG)
  - fix: adaptation in redundancy

Example: VLSI Analog-to-digital vector quantizer (Cauwenberghs and Pedroni, 1997)
Silicon Learning Machines for Embedded Sensor Adaptive Intelligence

Large-Margin Kernel Regression

Kerneltron: massively parallel support vector “machine” (SVM) in silicon (JSSC 2007)

Class Identification

MAP Forward Decoding

Sub-microwatt speaker verification and phoneme recognition (NIPS ’2004)

Sequence Identification

Analog

ASP

Digital

A/D

Sensory Features

Gini SVM
Trainable Modular Vision Systems: The SVM Approach

Papageorgiou, Oren, Osuna and Poggio, 1998

- Support vector machine (SVM) with mathematical foundations in Statistical Learning Theory (Vapnik, 1995)

- The training process selects a small fraction of prototype support vectors from the data set, located at the margin on both sides of the classification boundary (e.g., barely faces vs. barely non-faces)

Support vector machine (SVM) classification for pedestrian and face object detection
Trainable Modular Vision Systems: The SVM Approach

Papageorgiou, Oren, Osuna and Poggio, 1998

- The number of support vectors, in relation to the number of training samples and the vector dimension, determine the generalization performance.

- Both training and run-time performance are severely limited by the computational complexity of evaluating kernel functions.

ROC curve for various image representations and dimensions.
**Kerneltron: Adiabatic Support Vector “Machine”**

Karakiewicz, Genov and Cauwenberghs, 2007

- **1.2 TMACS / mW**
  - adiabatic resonant clocking conserves charge energy
  - energy efficiency on par with human brain ($10^{15}$ SynOP/S at 15W)

Classification results on MIT CBCL face detection data

Karakiewicz, Genov, and Cauwenberghs, VLSI’ 2006; CICC’ 2007
Resonant Charge Energy Recovery

CID array

![Diagram of resonant charge energy recovery system]

- **Vdd**
- **L**
- **V_HC(t)**
- **C**
- **pull**
- **ERL DRIVERS**
- **C-pdf**
- **V_HC(T)**
- **resonance**
- **capacitive load**

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**Graph:**

- **Energy (fJ/MAC)**
- **Data Probability Density**
- **Number of Active Inputs (capacitive load)**

- **MIT CBCL PDF**
- **Theoretical Dynamic CMOS**
- **Theoretical Adiabatic**
- **Simulated Dynamic CMOS**
- **Simulated Adiabatic**
- **Measured Dynamic CMOS**
- **Measured Adiabatic**

Legend:

- **Dynamic**
- **Adiabatic**
Sub-Micropower Analog VLSI Adaptive Sequence Decoding
Chakrabarty and Cauwenberghs, 2004

Silicon support vector machine (SVM) and forward decoding kernel machine (FDKM)

Forward decoding MAP sequence estimation

Biometric verification

840 nW power

GiniSVM
Adaptive Machine Intelligence

Training Machines towards Human Performance through Games

Competitive Games

Human Brain

Human and Machine Learning

Intelligent Machines

Internet

video
audio
VR

keyboard
mouse
joystick

game moves

events

Event Codec

Internet

game moves
Competitive Games: Humans and Machines

- Learning through experience in two-player zero-sum games:
  - Humans to humans: *Novices learn from experts to become experts.*
  - Humans to machines: *Towards human-level machine performance.*
  - Machines to machines: *Beyond human-level machine performance.*

- Heterogeneous competitive ranking:
  - *ELO score ranks humans and machines alike.*
  - *Turing test.*
Web-Based Competitive Games

Human Players

- Existing, extensively developed game infrastructure
- Readily available, large pool of human subjects
Web-Based Competitive Games

*Humans and Machines*

- Event codec adapter and machine interface
- Central logging, ranking, and matchmaking at external game server
Web-Based Competitive Games

*Humans Tutoring Machines*

- Machine learns by observing actions *and* internal representation (EEG brain activity) of human expert.
- Neuromorphic: trained machine approaches human brain function *and* form.
Extensions of Interface and Benchmark Infrastructure

**General Game Environments**

- **Game boxes**
  - Specialized computers with advanced graphics for games
    - Virtual game environments
    - Multi-player capable through internet
  - Examples:
    - Sony Playstation II
    - Microsoft Xbox 360
    - Nintendo Wii

- **Robots**
  - Physical interface to sensory input and motor output
    - Real-world game environments
  - Examples:
    - NSI Darwin
    - K-Team Khepera III
    - WowWee Robosapien
Closing the Loop: Interactive Neural/Artificial Intelligence

Neuromorphic Engineering

Learning & Adaptation

Micropower Mixed-Signal VLSI

Neuro Bio

Neurosystems Engineering

Adaptive Sensory Feature Extraction and Pattern Recognition

Biosensors, Neural Prostheses and Brain Interfaces
Computational modeling

**thalamocortical/BG model**

- **Coherence**
  - **Spearman's**
  - **DDO**
  - **DP**
  - **DH**
  - **SN**
  - **SNr**

- **PNS**
  - **PNS**
  - **PNS**
  - **PNS**
  - **PNS**
  - **PNS**

- **CNS**

- **MoBI**
  - **EEG**
  - **EMG**
  - **kinetics, gaze**

- **MoCap**
  - **CNS**
  - **PNS**

- **CyberGlove**

**METRIC fitness function Q**

- **MIMO parameters θ**

**PD markers**

- **adaptive control**

- **force**

- **synaptic plasticity**

**Experimental Setup**

- **EEG**
  - Cortical EEG sources
  - Thalamocortical sources
  - Hippocampal sources

**EEG brain dynamics and Parkinson's**

- **Cortical EEG sources**
  - Motor cortex
  - Somatosensory cortex

**EEG data in F3**

- **Average EEG**
  - Time vs. frequency

- **Experimental Setup**
  - Spike correlation and functional connectivity

**Neuromorphic emulation of brain dynamics in motor control**

**MoBI**

- **MoCap**
  - **CNS**
  - **PNS**

**Force feedback**
Brain Computer Interfaces and Motor Control

• The brain’s motor commands …
  - Parietal/frontal cortex
    • Implanted electrodes
    • Electroencephalogram (EEG)
      - Cortical signals, noninvasive
      - Low bandwidth (seconds)
  - Nerve signals
    • Spinal cord electrodes
    • Electromyogram (EMG)
      - Muscle signals, noninvasive
      - Higher bandwidth (milliseconds)

... translated into motor actions
  - Machine learning/signal processing
  - Neuromorphic approaches
    • Central pattern generators (CPGs)

Wireless Non-Invasive, Orthotic Brain Machine Interfaces

- Mind-machine interfaces for augmented human-computer interaction
- Body sensor networks for mobile health monitoring and augmented situation awareness

Yu Mike Chi, 2010 TATRC Grand Challenge
Wireless EEG/ICA Neurotechnology

with Tom Sullivan, Steve Deiss, Tzyy-Ping Jung and Scott Makeig

• Integrated EEG/ICA wireless EEG recording system
  – Scalable towards 1000+ channels
  – Dry contact electrodes
  – Wireless, lightweight
  – Integrated, distributed independent component analysis (ICA)
Wireless Non-Contact Biopotential Sensors

Mike Yu Chi and Gert Cauwenberghs, 2010

EEG alpha and eye blink activity recorded on the occipital lobe over a haired skull.
Non-Contact EEG Recording over Haired Scalp


- Easy access to hair-covered areas of the head without gels or slap-contact
- EEG data available only from the posterior
  - P300 (Brain-computer control, memory recognition)
  - SSVP (Brain-computer control)
Non-Contact vs. Ag/AgCl Comparison

Subject’s eyes closed showing alpha wave activity
Full bandwidth, unfiltered, signal show (.5-100Hz)
EEG/ECoG/EMG Amplification, Filtering and Quantization
Mollazadeh, Murari, Cauwenberghs and Thakor (2009)

- **Low noise**
  - $21\text{nV/Hz}$ input-referred noise
  - $2.0\mu\text{Vrms}$ over $0.2\text{Hz}-8.2\text{kHz}$

- **Low power**
  - $100\mu\text{W}$ per channel at $3.3\text{V}$

- **Reconfigurable**
  - $0.2-94\text{Hz}$ highpass, analog adjustable
  - $140\text{Hz}-8.2\text{kHz}$ lowpass, analog adjustable
  - $34\text{dB}-94\text{dB}$ gain, digitally selectable

- **High density**
  - 16 channels
  - $3.3\text{mm} \times 3.3\text{mm}$ in $0.5\mu\text{m}$ 2P3M CMOS
  - $0.33$ sq. mm per channel

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Mouse scalp EEG after cardiac arrest

Macaque auditory cortex extracellular spike recording
Distributed Sensing of Dopamine Activity
Murari, Stanacevic, Cauwenberghs, and Thakor (2005)

Electrochemical detection
Carbon-probe redox current

“In vitro” Dopamine monitoring by the chip using micro-fabricated electrode array as working electrode.

Carbon electrodes for Dopamine sensing (Murari, Rege, Paul, and Thakor, 2002)

VLSI potentiostat array for distributed electrochemical sensing (Murari, Stanacevic, Cauwenberghs, and Thakor, 2004)
"In vitro" nitric oxide (NO) sensing
  - emulation of the shear stress regulated NO release pathway observed in endothelial cells
  - current observed by multi-channel VLSI potentiostat
Implantable probe with electrochemical sensors, VLSI potentiostat and power harvesting telemetry chip.

Power delivery and data transmission over the same inductive link
Cortical Surface Microvascular and Functional Imaging

with K. Murari, N. Thakor, J. Driscoll, D. Kleinfeld and T. Sejnowski

Laser speckle functional imaging of microvascular neural activity on cortical surface, through thinned skull.

Laser speckle sub-wavelength imaging for non-invasive target/sample surface reconstruction and identification.

Two-photon imaging of blood flow in cortical surface microvessels.

Two-photon imaging of blood flow in cortical surface microvessels.
CMOS Imaging in Awake Behaving Rats
Murari, Etienne-Cummings, Cauwenberghs, and Thakor (2010)

- First simultaneous behavioral and cortical imaging from untethered, freely-moving rats.
Integrated Systems Neuroengineering

Neuromorphic/Neurosystems Engineering

Neural Systems

Learning & Adaptation

Human/Bio Interaction

Environment

Silicon Microchips

Sensors and Actuators