BENG 207 Special Topics in Bioengineering

Neuromorphic Integrated Bioelectronics

Week 3: Silicon Cochlea

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http://isn.ucsd.edu/courses/beng207
# BENG 207 Neuromorphic Integrated Bioelectronics

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<td>10/28, 11/1</td>
<td>Review. Modular and scalable design for neuromorphic and bioelectronic integrated circuits and systems. Design for full testability and controllability.</td>
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<td>11/8, 11/10</td>
<td>Learning and adaptation to compensate for external and internal variability over extended time scales. Background blind calibration of device mismatch. Correlated double sampling and chopping for offset drift and low-frequency noise cancellation.</td>
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<td>11/22, 11/24</td>
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<td>11/29, 12/1</td>
<td>Project final presentations. All are welcome!</td>
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Mixed-Signal VLSI Robust Time-Frequency Feature Extraction

Sensory Features → Continuous-Time Analog → ASP → Asynchronous Digital → A/D

Cochlear Filterbank → Robust Speaker Recognition
Pushing the Analog-Digital Boundary

- **Digital Sensory Processing:**
  - General-purpose
  - High precision (limited by A/D)

- **Analog and Mixed-Signal Sensory Processing:**
  - “Smart” A/D
  - Low power
  - Low complexity
Event-Driven Sensory Analog Processing

- **Data driven**
  - Communication bandwidth adjusts to information bandwidth in the signal

- **Asynchronous**
  - No quantization (binning) of time
  - No power-hungry clocks and synchronization across network nodes

- **Highly energy efficient**
  - Significant energy savings over Nyquist sampling for signals of sparse activity and medium amplitude resolution

- **Robust to additive noise in the signal**
Multi-Modal Event-Driven Sensory Analog Processing

- Asynchronous routing of sensory address events
- Expandable dimensionality and integration of multiple sensory modalities
- Reconfigurable and adaptive general-purpose signal processing and identification
Auditory Anatomy and Modeling

Normal Hearing:
• **Outer ear** receives incoming acoustic wave
• **Middle ear** converts sound to mechanical vibration
• **Inner ear:** **cochlea** (a snail-shaped cavity filled with fluid), mechanical vibration -> fluid vibration -> displacement of **basilar membrane** (frequency information coding) -> bending of **hair cells**, releases neurochemicals -> firing of **auditory neuron** -> **central nervous system** (brain)

Abstraction for Speech Recognition:
• **MFCC**: Pre-emphasis, Mel-scale filter, Static nonlinear compression.
• Auditory perception model: + adaptive compression
- Inner hair cells excited by basilar membrane vibrations, amplified by outer hair cells, stimulate cochlear nerve fibers in the healthy cochlea.
- Electrodes in the cochlear implant stimulate cochlear nerve fibers with alternating current signals, of amplitude representative of sound intensity.

Silicon Cochlea and Auditory Periphery

- Fluid-filled cochlea transduces sound to resonant mechanical vibrations of the basilar membrane
  - *Characteristic frequency-space coding*
- Hair cells transduce membrane deflections to auditory nerve impulses
  - *Amplitude and time encoding with spikes*
Silicon Cochlea and Auditory Periphery
Kumar, Cauwenberghs, and Andreou (1997)

Hair Cell

Basilar Membrane
Auditory Zero-Crossing Feature Extraction Chip
Kumar, Himmelbauer, Cauwenberghs, and Andreou (1998)
Auditory Zero-Crossing Feature Extraction Chip
Kumar, Himmelbauer, Cauwenberghs, and Andreou (1998)

- 2mm X 2mm in 1.2μm CMOS
- 15 frequency channels
- asynchronous “spiking,” address-event communication

2.2mm

2.25mm

BENG 207 Neuromorphic Integrated Bioelectronics

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Auditory Zero-Crossing Feature Extraction Chip
Kumar, Himmelbauer, Cauwenberghs, and Andreou (1998)

- Asynchronous (“spike”) event features:
  - Zero-crossing intervals
  - Energy
- Linear discriminant analysis (LDA) transformed features are directly suitable for use with hidden Markov models (HMM) in speech recognition:
  - 99.47% recognition accuracy on TI-DIGITS
  - More robust to additive noise than mel-scale cepstral features
Time-frequency sensory event stream encoders:

- Convert a continuous-time analog sensory input, such as an acoustic signal, into an output stream of spike time events.
- Time events correspond to time instances of zero-crossings of bandpass filtered versions of the signal.
- Each bandpass filter with different center frequency is coded as a frequency address in the zero-crossing time event stream for distributed time-frequency encoding.
Integrated Pattern Recognition Adaptive Microsystems

Ubiquitous sensing and computing:

Adaptive, Mobile, Sensory systems
Real-time, Low-power, Robust feature extraction
Parallel, Analog, Biomimetic computing
Time-Frequency Feature Extraction

Time-Frequency Analysis Methods

- **Short-Time Fourier Transform (STFT)**
  Time-Frequency resolution limitation

- **Wavelet Transform**
  Multi-scale decomposition
  Better time frequency resolution

- **Filter Banks**
  Continuous time (no windowing)
  Multi-resolution (constant Q filter bank)

Which features to use?

- Application dependent
  speech / speaker / gender / emotion / language, .../ recognition,

- **Domain knowledge and methods combination**
  MFCC (Mel-frequency cepstral coefficients) features
  Combine auditory knowledge, SFTF, filter banks, ...

- **Feature selection**
  Maximize information content in feature extraction (Kumar’ 96, Padmanabhan’ 05)
  Experimental evaluation
Feature Extraction Chip Architecture

- Configurable parallel and cascade filter bank architecture
- 32 individually programmable channels:
  - Each channel: 2 biquad stages, full wave rectifier, and 1\textsuperscript{st} order low-pass filter
    - biquad: programmable center frequency and Q-factor
    - low-pass filter: programmable cut-off frequency
Electronic Cochlea
Lyon and Mead (1988)

Operational transconductance amplifier (OTA)

First-order section
\[
\frac{V_2}{V_1} = \frac{1}{\tau s + 1}
\]
\[\tau = C/G\]

Second-order section
\[
H(s) = \frac{V_3}{V_1} = \frac{1}{\tau^2 s^2 + 2\tau s (1 - \alpha) + 1}
\]
\[\tau = C/G \text{ and } \alpha = G_3/(G_1 + G_2)\]

Programmable Fully Differential OTA-C Filter

Fully differential OTA

Second Order Band Pass and Low Pass Filter

\[ H_{bp}(s) = \frac{s G_1 C_1}{s^2 + s \frac{G_2 C_1}{C_1 C_2} + \frac{G_3 G_4}{C_1 C_2}} \quad \omega = \sqrt{\frac{G_3 G_4}{C_1 C_2}} \]

\[ H_{lp}(s) = \frac{G_1 G_3}{s^2 + s \frac{G_2 C_1}{C_1 C_2} + \frac{G_3 G_4}{C_1 C_2}} \quad Q = \sqrt{\frac{C_1 G_3 G_4}{C_2 G_2^2}} \]

- Filter parameters (center frequency, quality factor, cut-off frequency) are a function of \( Gm \) and \( C \)
- Programmable \( Gm \) and selectable value of capacitance.
Three Decades Programmable OTA

**Fully differential configuration**
- Doubled dynamic range, SNR
- Elimination of even order distortion
- High power supply rejection ratio (PSRR)
- Immunity to bias noise and variation

**Differential pMOS input stage**
- High input common mode rejection ratio
- Low 1/f noise

**Integrated resistor source degeneration**
- Wide input linear dynamic range

**Multi-stage current scaling**
- Multi-resolution, three decades $G_m$ tuning

**Cascode structure**
- High output impedance
Current Scaling

Coarse: 2-bit mirror with selectable W/L ratio 1:1, 1:2, 1:4, 1:8

Fine: 8-bit current divider
- Compact, four transistors per bit
- Wide current range
- Requires precise conveyer circuit to set \( V_a \) and \( V_b \) at equal voltage

\[
I_{out} = I_{in} \sum_{i=1}^{n} B_i 2^{-i}
\]

Regulated Cascode Circuit

- Current conveyor
- Equates voltages \( V_a \) and \( V_b \)
- Low input impedance

\[
Z_{in} = \frac{1}{G_{m,6}(1 + G_{m,2}A_{cg,4}R_{out})}
\]

- High output impedance

“A packaged low-noise high-speed regulated cascode transimpedance amplifier using 0.6 N-well CMOS technology” Sung Min Park and C. Toumazou, ESSCC, 2000.
Common Mode Feedback Circuit

- High common mode gain
- Low differential mode gain
- $V_{cm}$ sets common mode of $V_n$ and $V_p$ to $V_{ref}$
- $V_{ref}$ is chosen to maximize linear dynamic range of OTA

“Design procedures for a fully differential folded-cascode CMOS operational amplifier”
**Silicon Implementation**

- **32-channel filter banks**
  - Parallel and cascaded configurable topologies
  - Total of 64 biquads and 32 first-order sections

- **Programmable filter parameter**
  - 320 OTAs with digitally programmable Gm
  - 180 capacitors with digitally selectable C
  - Cut-off/center frequency range: 100Hz-100KHz
  - Q range: 0.5-5

- **0.5um, 2P3M CMOS**
  - 3mm X 3mm
  - 9mW power

Photomicrograph of feature extraction chip
OTA Linear Range and Programmability

- Wide differential linear range, 2.4Vpp
- Wide common mode range, > 2V
- High common model rejection ratio, 40dB

- Multi-resolution programming, coarse 2 bits, fine 8 bits
- Wide programming range 1/2048
# OTA Performance Summary

<table>
<thead>
<tr>
<th>Parameter Specification</th>
<th>Measured</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max $Gm$</td>
<td>0.8 $\mu$A/V</td>
</tr>
<tr>
<td>Min $Gm$</td>
<td>0.39 nA/V</td>
</tr>
<tr>
<td>Programming ratio</td>
<td>1/2048</td>
</tr>
<tr>
<td>Input offset voltage</td>
<td>20 mV</td>
</tr>
<tr>
<td>Max dynamic input range</td>
<td>2.4 $V_{pp}$</td>
</tr>
<tr>
<td>Third order harmonic distortion</td>
<td>-48 dB @ $1V_{pp}$</td>
</tr>
<tr>
<td>Common mode input voltage range</td>
<td>0.5-3 V</td>
</tr>
<tr>
<td>Common mode output voltage range</td>
<td>1.0-4.0 V</td>
</tr>
<tr>
<td>Common mode rejection ratio</td>
<td>40 dB</td>
</tr>
<tr>
<td>Power consumption</td>
<td>10 $\mu$W</td>
</tr>
<tr>
<td>Silicon area</td>
<td>0.014 mm$^2$</td>
</tr>
<tr>
<td>Power supply</td>
<td>5 V</td>
</tr>
</tbody>
</table>

Filter Parameter Sensitivity Analysis

\[ f_o = \frac{1}{2\pi} \sqrt{\frac{G_3 G_4}{C_1 C_2}} \]
\[ Q = \sqrt{\frac{C_1 G_3 G_4}{C_2 G_2^2}} \]
\[ A_{bp} = \frac{G_1}{G_2} \]
\[ \delta f_o = \frac{f_o}{2} \left( \frac{\delta G_3}{G_3} + \frac{\delta G_4}{G_4} + \frac{\delta C_1}{C_1} + \frac{\delta C_2}{C_2} \right) \]
\[ \delta Q = Q \left( \frac{\delta G_2}{G_2} + \frac{\delta G_3}{2G_3} + \frac{\delta G_4}{2G_4} + \frac{\delta C_1}{C_1} + \frac{\delta C_2}{C_2} \right) \]
\[ \delta A_{bp} = A_{bp} \left( \frac{\delta G_1}{G_1} + \frac{\delta G_2}{G_2} \right) \]

Multi-resolution programming, to minimize sensitivity of center frequency.

Define
\[ G^* = 2\pi f_o \sqrt{C_1 C_2} \]

If \( G^* \in (0, g] \cup (\sqrt{2} g, 2g) \cup (2\sqrt{2} g, 4g) \cup (4\sqrt{2} g, 8g) \) choose \( G_3 = G_4 = G^* \)

Otherwise, \( G_3 = G^*/\sqrt{2} \), \( G_4 = \sqrt{2} G^* \)
Filter Parameter Non-idealities

Non-idealities of OTA: offset, limited linear range, finite output impedance, finite common mode rejection, …

\[
\begin{align*}
    f_o &= \frac{1}{2\pi} \sqrt[\,]{\frac{G_3 G_4}{C_1 C_2}} \\
    Q &= \sqrt[\,]{\frac{C_1 G_3 G_4}{C_2 G_2^2}} \\
    A_{bp} &= G_1 / G_2
\end{align*}
\]

Finite OTA output impedance

Ideal, independently programmable

Filter parameters are no longer independently programmable

• OTA nonlinear macro model (Gomez’ 95)

• Response surface method for continuous time filter (Malik’ 05)

Implemented

Generalized linear model for filter parameter modeling and calibration
Filter Parameter Modeling and Calibration

• Generalize Linear Model:

\[
\log f_o = a_0 + a_1 \log G_1 + a_2 \log G_2 + a_3 \log G_3 + a_4 (\log G_1)^2 + \\
a_5 \log G_1 \log G_2 + a_6 \log G_1 \log G_3 + a_7 (\log G_2)^2 + \\
a_8 \log G_2 \log G_3 + a_9 (\log G_3)^2 + a_{10} (\log G_1)^3 + \ldots
\]

\[
\log Q = b_0 + b_1 \log G_1 + b_2 \log G_2 + b_3 \log G_3 + b_4 (\log G_1)^2 + \ldots
\]

\[
\log A_{bp} = c_0 + c_1 \log G_1 + c_2 \log G_2 + c_3 \log G_3 + c_4 (\log G_1)^2 + \ldots
\]

Modeling procedure:

1. Data sample schema: choose modeling region of interest, given target characteristic determine least sensitivity values for programming bits.
2. Sample data: program filter, sweep frequency, measure filter parameters.
3. Build Model: determine \(a(i), b(i), c(i)\) by least squares error linear regression.

Calibration:

\[
\arg \min_{\log G_i} \left\{ W_f (\log f_o - \log(T_F))^2 + W_Q (\log Q - \log(T_Q))^2 + W_A (\log A - \log(A))^2 \right\}
\]

\[
\log(2^{S_0 S_1}) \leq \log G_i \leq \log(2^{255} \cdot 2^{S_0 S_1})
\]
Gm-C Filter Response

Measured and predicted response

- programmable center frequency, Q, gain, and cut-off frequency.
- programming range:
  - CF: 100Hz-100 kHz;
  - Q: 0.5-5.
# Biquad Performance Summary

<table>
<thead>
<tr>
<th>Parameter Specification</th>
<th>Measured</th>
</tr>
</thead>
<tbody>
<tr>
<td>Filter type</td>
<td>second order bandpass and low-pass</td>
</tr>
<tr>
<td>Center Frequency</td>
<td>100 KHz</td>
</tr>
<tr>
<td>Silicon area</td>
<td>0.06 mm²</td>
</tr>
<tr>
<td>Power consumption</td>
<td>100 μW (@1Vpp input)</td>
</tr>
<tr>
<td>Input referred noise</td>
<td>865μV</td>
</tr>
<tr>
<td>Differential input range</td>
<td>2V_{pp} (@THD=-42dB)</td>
</tr>
<tr>
<td>Dynamic range</td>
<td>61 dB (@THD=-42dB)</td>
</tr>
<tr>
<td>Stop-band rejection</td>
<td>32 dB (for low-pass)</td>
</tr>
<tr>
<td>Passband ripple</td>
<td>0.24 dB (for low-pass)</td>
</tr>
<tr>
<td>CMRR</td>
<td>40 dB</td>
</tr>
<tr>
<td>PSRR</td>
<td>39 dB</td>
</tr>
</tbody>
</table>
Application: Robust Speech Recognition

Speech segment with various samples of additive noise from NOISEX-92 database, at 10dB SNR.

- **Clean**

- **Factory**

- **White**

- **Car**

- **Babble**
Auditory Perception Model

- **Pre-emphasis**: middle ear, 50Hz highpass cut-off
- **1st Band-pass**: basilar membrane; frequency tuned place coding
- **Full-wave rectifier**: hair cell; extracts magnitude envelope information
- **Log**: static non-linear compression
- **2nd Band-pass**: adaptive non-linear compression (Tchorz 99).
MFCC vs. Auditory Features on Isolated TI-Digit Database

Experiment conditions:
- 14 states left to right hidden Markov model (HMM) for each digit
- 12 dimension feature by discrete cosine transform (DCT)
- 4 mixture Gaussian model
- 770 clean training utterances
- Tested on 440 utterances added with noise of different statistics
- Hidden Markov model toolkit (HTK)

Training:
Maximum likelihood parameter estimation through Expectation Maximization (EM) algorithm

Testing:
$\text{argmax}\{P(W|O)\}$, Bayes rule
Experimental Results

YOHO Text-independent Speaker Recognition

‘Yoho’ speech identification database
- 6 continuous digits per utterance
- 10 male speakers are chosen
- 30 clean utterances per speaker for enrollment
- 20 utterances per speaker for identification

Speech Feature
- Clean speech, and speech with additive noise of various statistics
- 12 dimensional feature vectors, MFCC vs. auditory model (Q1=7)
- Different from features used for speech recognition (Q1=4)

Training and Testing
- Trained on clean speech, tested on clean and noisy speech
- Gaussian mixture model with 32 mixtures
- Expectation-Maximization (EM) algorithm for training

\[
p(x | \lambda) = \sum_{i=1}^{M} p_i b_i(x)
\]

\[
b_i(x) = \frac{1}{(2\pi)^{D/2} | \sum_i |^{1/2}} exp\left\{ -\frac{1}{2} (x - \mu_i)^T (\sum_i)^{-1} (x - \mu_i) \right\}
\]
Text-independent Speaker Identification Results

- **Car noise**
- **Babble noise**
- **Factory noise**
- **White noise**
Event-Driven Sensory Adaptive Analog Processing

- Data driven
- Asynchronous
- Highly energy efficient
- Robust to additive noise in the signal
- Asynchronous routing of sensory address events
- Expandable integration of sensory modalities
- Reconfigurable and adaptive general-purpose signal processing and identification

Time-frequency sensory event stream encoder

Spatiotemporal sensory event stream encoder

AER time events

TDMA Asynchronous Bus

AER time events

Event stream transceiver and decoder

Classification events
e.g. detection of glass break acoustic events

e.g. filterbank zero-crossings

e.g. spatial gradient and temporal change amplitude threshold detections

Continuous-Time Analog

Sensor

Asynchronous Digital

Sensor

ASP

A/D

ADSP
Acoustic Source Separation and Localization

Bioinspired Smart Sensing Adaptive Microsystems

Biomorphic and Neuromorphic Engineering

Sub-Wavelength Tympanal Directional Hearing

Adaptation

Micropower Mixed-Signal VLSI

Micropower, low-aperture acoustic source localization (ISCAS’2004)

Tympanic directional hearing (parasitoid fly)
Parasitoid fly localizes singing cricket by a beamforming acoustic sensor of dimensions a factor 100 smaller than the wavelength.

Tympanal beamforming organ senses acoustic pressure gradient, rather than time delays, in the incoming wave.

Auditory Anatomy and Temporal Acoustic Cues

(A) The auditory organs of the parasitoid fly *Ormia ochracea* are located on the anterior thorax, between the first pair of legs (L) and the neck (N). The tympanal membranes (TM) are adjacent to each other and set close together by the midline of the animal (vertical dashed line). Providing a connection between the two TMs across the midline, the intertympanal bridge is made of thicker cuticle than TMs and has the shape of a coat hanger. Two depressions at both ends of the intertympanal bridge indicate the insertion point of the sensory organs (arrows). Arrows also point to the interaural distance.

(B) Interaural time difference (ITD) as a function of the angle of incidence of the sound stimulus. Right ordinate: ITDs calculated for humans (ear separation of 170 mm). Left ordinate: ITDs at the fly’s ears calculated for an interaural distance of 0.6 mm. Data point (with standard deviation) shows ITD measurement made at -90° azimuth and 5 kHz tone, with two probe microphones located at the TMs.

Mechanical Coupling Across the Intertympanal Bridge

(A) Close-up of the intertympanal bridge connecting the tympanal membranes.

(B) Simple mechanical model of the bridge as a seesaw endowed with two rigid bars connected by a flexible central hinge (~).

(C) On the basis of the laser vibrometric micromechanical analysis, it is suggested that two basic modes can characterize the observed mechanical response. Bending occurred at low frequencies (mode 1; <4 kHz), whereas rocking was measured at intermediate frequencies (mode 2; 5–7 kHz). At higher frequencies (15 kHz and above), bending and rocking modes combine to elicit motion in one tympanum only (mode 1 + 2).

Traveling Wave Gradients

- For closely spaced acoustic sensors ("ears") as in the *Ormia*, interaural time delays (ITDs) are too short to be resolved with neural circuits.
- For sensor spacing closer than a wavelength (coherence interval), measurement of interaural level differences (ILDs) yields estimates of the ITDs, scaled by the time derivative of the acoustic signal.
Gradient Flow Localization

- **Gradient flow** obtains time delays at sub-sampling resolution by relating spatial and temporal differentials of the field across the array.
- 3-D direction cosines are obtained from a planar geometry with four sensors.
Gradient Flow Localization and Separation

- Gradient signals from multiple sources add linearly. Sources are separated and localized with independent component analysis (ICA).

\[ \frac{d}{dt} \begin{bmatrix} \xi_{00} \\ \xi_{10} \\ \xi_{01} \end{bmatrix} \approx \sum_{\ell} \tau_{\ell} \dot{s}_{\ell}(t) \]

Barrere and Chabriel, IEEE TCAS-I, 2002
Cauwenberghs, Stanacevic and Zweig, ISCAS ’2001
Differential Sensitivity

- Gradient flow bearing resolution is fundamentally independent of aperture
  - Cramer-Rao bound
  - Assumes interference noise dominates sensor/acquisition noise
- In practice, aperture is limited by differential sensitivity in gradient acquisition
  - Enhanced through differential coupling
    - Mechanical
      - Intertympanal bridge [Robert, Miles and Hoy, 1996]
    - Electrical
      - Latency/population encoding in auditory afferents [Oshinsky and Hoy, 2002]
Auditory Afferents in the *Ormia ochracea*

- **Latency Encoding**

- **Population Encoding**

Gradient Flow Super-Resolution Delay Estimation

- $\sin(\omega t)$
- $\sin(\omega (t-\tau))$  
- $\sin(\omega (t-\tau))$

- 200 Hz signal
- 2 kHz sampling frequency
- 2 µs delay resolution
GradFlow/ASU Localization Experiments

- **Acoustic Surveillance Unit (ASU)**  
  *Riddle et al., 2004*

- **Integrated GradFlow ASIC**  
  *Stanacevic and Cauwenberghs, ESSCIRC’2003*

- **DARPA Aberdeen Proving Grounds field test:**
  - Sensor network with 3 ASUs
  - 5 degree bearing accuracy in tracking ground vehicles over 600m range
  - Tracked azimuth & elevation of overflying aircraft

- **GradFlow ASIC**
  - 200 nsec resolution
  - 16 kHz sampling
  - 54 µW power
  - 3mm x 3mm in 0.5µm 3M2P CMOS
Gradient Flow Source Separation and Localization

Gradient flow on a mixture of acoustic waves reduces to a static (noisy) mixture problem:

\[ \frac{d}{dt} \begin{bmatrix} \xi_{00} \\ \xi_{10} \\ \xi_{01} \end{bmatrix} = \begin{bmatrix} 1 & \cdots & 1 \\ \tau_1^L & \cdots & \tau_1^L \\ \tau_2^L & \cdots & \tau_2^L \end{bmatrix} \begin{bmatrix} s_1(t) \\ \vdots \\ s_L(t) \end{bmatrix} + \begin{bmatrix} \nu_{00} \\ \nu_{10} \\ \nu_{01} \end{bmatrix} \]

\( x = A \) \( s + n \)

solved by linear static ICA (Independent Component Analysis)

Sources

Gradients

Reconstructed sources

Mixing matrix

Unmixing matrix

\( s(t) \) \( x(t) \) \( y(t) \)
Gradient Flow Independent Component Analysis

integrated acoustic source separation and localization

GradFlow ASIC

waves

ITD

\[ s(t + \tau) \]

ILD

\[ \tau \hat{s}(t) \]

\[ j \]

\[ \xi_{01} \]

\[ \xi_{00} \]

\[ \xi_{10} \]

\[ \tau_1 \]

\[ \tau_2 \]

\[ t \]

\[ \tau \]

ITD

ILD

\[ ^\wedge S_1 \]

\[ ^\wedge S_2 \]

sources

\[ 54 \mu W \text{ power} \]

\[ 180 \mu W \text{ power} \]

1.5 m

1 cm

\[ 1 \text{ cm} \]

3 mm

3 mm

3 mm

54 \mu W power

180 \mu W power

\[ 1.5 \text{ m} \]

\[ 1.5 \text{ m} \]

\[ 3 \text{ mm} \]

\[ 3 \text{ mm} \]

\[ 3 \text{ mm} \]

\[ t \]

\[ \tau \]

\[ \tau \]

\[ \tau \]

\[ t \]

\[ t \]
Gradient Flow ICA Residuals

crosstalk

\[ \hat{\mathbf{s}}_1 \]
\[ \hat{\mathbf{s}}_2 \]

\textit{estimates}

Sources

\( S_1 \)

\( S_2 \)

Contribution of source 1 to 1

Contribution of source 1 to 2

\(-11.7\text{dB}\)

Contribution of source 2 to 1

Contribution of source 2 to 2

\(-12.7\text{dB}\)
Crosstalk is virtually free of the direct path

- **Reverberation can be eliminated using LMS adaptive filtering of the ICA outputs**
- **Direction cosines of recovered sources correspond to the direct path**
Hearing Aid Implications

- Gradient flow localizes sources in three dimensions, and produces a linear instantaneous mixture of the sources that is conveniently separated using independent component analysis (ICA).

- ICA leads to adaptive suppression of several sources of noise and unwanted signals, independent of their angle of arrival.

- Gradient flow combined with ICA offers more flexibility in the choice of signal to be amplified and presented to the listener. The signal can be chosen based on the direction of arrival with respect to microphone array, or based on the power of the signal.
Directional Selectivity in Hearing Aids

• ‘State of the Art’
  - Two microphones allow for one null angle in directionality pattern
  - Adaptive beamforming allows to steer the null to noise source
  - Presence of multiple noise sources requires source localization and separation with multiple microphones

http://www.oticon.com
Gradient Flow ICA Microphone

Differential Mechanical Sensing
Ron Miles, SUNY Binghamton
- MEMS microphone
- Models Ormia’s inter-tympanal bridge mechanical coupling

Differential Optical Transduction
Levent Degertekin, Georgia Tech
- Optical microphone
- Diffractive optical sensing of membrane displacement
- Improved sensitivity and noise (<20dB spl)

Differential Electronic Signal Processing
- Gradient flow amplification
- ICA separation and localization
- Micropower chips (<250 uW)
Opportunities for In-Ear Health Sensing

• Prevalence of wireless personal audio devices:

• Rapidly aging global population:
  – Over the next few decades, people 65 years and older will account for **20% of the global population**, an unprecedented shift. New healthcare challenges and opportunities will arise for which **reliable and continuous high-bandwidth health data** will be critical.

• In-Ear Health Sensing Platform
  – An in-ear healthcare platform has the convenience, comfort, and discretion of a consumer audio device, while offering valuable electrophysiological and biochemical data.
In-Ear Electrophysiology
Paul et al, IEEE NER 2019; IEEE EMBC 2019

High-density dry-contact electrodes capture a wealth of physiological information from an integrated in-ear device

- In-ear, high-density dry-contact electrode recording platform records electroencephalography (EEG) signals from the brainstem, temporal, and visual cortices with quality comparable to commercial scalp EEG.
- Electrical impedance measurement provides electrodermal activity (EDA).
- Opportunities for closed-loop auditory neurofeedback (tinnitus, insomnia, apnea, etc).


Event-Driven Sensory Adaptive Analog Processing

- Data driven
- Asynchronous
- Highly energy efficient
- Robust to additive noise in the signal

- Asynchronous routing of sensory address events
- Expandable integration of sensory modalities
- Reconfigurable and adaptive general-purpose signal processing and identification
# BENG 207 Neuromorphic Integrated Bioelectronics

<table>
<thead>
<tr>
<th>Date</th>
<th>Topic</th>
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<tbody>
<tr>
<td>10/11, 10/13</td>
<td>Silicon cochlea. Low-noise acoustic sensing and automatic gain control. Continuous wavelet filter banks. Interaural time difference and level difference auditory localization. Blind source separation and independent component analysis.</td>
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<tr>
<td>10/28, 11/1</td>
<td>Review. Modular and scalable design for neuromorphic and bioelectronic integrated circuits and systems. Design for full testability and controllability.</td>
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<td>11/8, 11/10</td>
<td>Learning and adaptation to compensate for external and internal variability over extended time scales. Background blind calibration of device mismatch. Correlated double sampling and chopping for offset drift and low-frequency noise cancellation.</td>
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<td>11/22, 11/24</td>
<td>Guest lectures</td>
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<td>11/29, 12/1</td>
<td>Project final presentations. All are welcome!</td>
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