Compressively Sensing Action Potentials (Neural Spikes)

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In collaboration with UCLA Neuroscience
Full Implantability
Full Implantability

Put the exam room IN the patient!
Raw Signal from a Depth Electrode
Signal Band Pass Filtered to Enhance Spikes

Signal from Extracellularly Implanted Depth Electrode (28Ksps)

Filtered Depth Electrode Signal 300 Hz – 3 KHz

Filtering
Spike Detection

These spikes are from multiple neurons in the vicinity of the electrode.
Spike Alignment

Action Potential (Spikes) Detected from Filtered Signal

Aligned Spikes
Spike Sorting

Aligned Spikes

Sorted Spikes

Sorting
Traditional Wireless Neural Recording Process

In vivo

1. Amplify and Digitize
2. Band Pass Filter
3. Spike Detect and Align
4. Radio TX

Ex vivo

1. Radio RX
2. Spike Sorting

[Diagram showing the process with brain images and signal waveforms]
CS Neural Recording Process

**In vivo**

1. Amplify and Digitize
2. Band Pass Filter
3. Spike Detect and Align
4. Compressive Sampling
5. Radio TX

**Ex vivo**

1. Radio RX
2. CS Recovery
3. Spike Sorting
4. Add Support
Two Features Useful for Compressed Sensing

- Spikes are compressible in the wavelet domain
- Spikes from the same neuron are similar in morphology
Representing the Spike in DWT Domain

Few large coefficients in DWT domain -- compressible
Number of Significant Coefficients (Support) in DWT Domain

Sparsity of EEG spikes of length 64. Mean=11.48

Histogram of Sparsity
Sparsity Inducing Transform

\[ \chi \]

\[ n \]
Sparsity Inducing Transform

DWT - $\Psi$

$\chi$
Sparsity Inducing Transform

\[ z = \Psi x \]

DWT - \( \Psi \)
A Visual Tour of Compressed Sensing

\[ \chi \]

\[ n \]
A Visual Tour of Compressed Sensing

\[ \Phi \]

\[ \chi \]

\[ \begin{array}{c}
  m \\
  n
\end{array} \]
A Visual Tour of Compressed Sensing

\[ \Phi \]

\[ y = \Phi x \]
Compressed Sensing Recovery

\[ y \]

\[ m \]
Compressed Sensing Recovery

\[
\hat{z} = \arg\min_{\tilde{z}} \frac{1}{2} \left\| y - \Phi \Psi^{-1} \tilde{z} \right\|_2^2 + \lambda \left\| \tilde{z} \right\|_1
\]
Compressed Sensing Recovery

\[ \hat{z} = \arg\min_{\tilde{z}} \frac{1}{2} \left\| y - \Phi \Psi^{-1} \tilde{z} \right\|_2^2 + \lambda \left\| \tilde{z} \right\|_1 \]

\[ \hat{x} = \Psi^{-1} \hat{z} \]
CS Neural Recording Process

**In vivo**

1. Amplify and Digitize
2. Band Pass Filter
3. Spike Detect and Align
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5. Radio TX

**Ex vivo**

1. Radio RX
2. CS Recovery
3. Spike Sorting

In vivo process includes:
- Amplify and Digitize
- Band Pass Filter
- Spike Detect and Align
- Compressive Sampling
- Radio TX

Ex vivo process includes:
- Radio RX
- CS Recovery
- Spike Sorting
Conventional Basis Pursuit Results

- 35.7 measurements for 20dB SNDR
- 18x → 26x compression

Median over 0.6M spikes
1st Quartile
3rd Quartile
Two Features Useful for Compressed Sensing

- Spikes are compressible in the wavelet domain
- Spikes from the same neuron are similar in morphology
Similarity in Neural Spikes

64 Sample Window of Two Neural Spikes

Comparing DWT Supports of Two Spikes

Little support mismatch, Mismatch at low values
Incorporating Similarity in CS Recovery

Basis Pursuit Recovery

\[ \hat{z} = \arg \min_{\tilde{z}} \frac{1}{2} \| y - \Phi \Psi^{-1} \tilde{z} \|_2^2 + \lambda \| \tilde{z} \|_1 \]

\( \Phi \) - Sampling matrix
\( \Psi \) - Sparsifying transform
\( \lambda \) - L1 penalizing factor
Incorporating Similarity in CS Recovery

Basis Pursuit Recovery

\[ \hat{z} = \arg\min_{\tilde{z}} \frac{1}{2} \| y - \Phi \Psi^{-1} \tilde{z} \|_2^2 + \lambda \| \tilde{z} \|_1 \]

- \( \Phi \) - Sampling matrix
- \( \Psi \) - Sparsifying transform
- \( \lambda \) - L_1 penalizing factor

**Masked** Basis Pursuit Recovery

\[ \hat{z} = \arg\min_{\tilde{z}} \frac{1}{2} \| y - \Phi \Psi^{-1} \tilde{z} \|_2^2 + \lambda \| \tilde{z}_{T^c} \|_1 \]
Incorporating Similarity in CS Recovery

Basis Pursuit Recovery

$$\hat{z} = \text{argmin}_{\tilde{z}} \frac{1}{2} \left\| y - \Phi \Psi^{-1} \tilde{z} \right\|_2^2 + \lambda \left\| \tilde{z} \right\|_1$$

\(\Phi\) - Sampling matrix
\(\Psi\) - Sparsifying transform
\(\lambda\) - \(L_1\) penalizing factor

**Masked** Basis Pursuit Recovery

$$\hat{z} = \text{argmin}_{\tilde{z}} \frac{1}{2} \left\| y - \Phi \Psi^{-1} \tilde{z} \right\|_2^2 + \lambda \left\| \tilde{z}^{Tc} \right\|_1$$

\(T\) - Set of support indices expected in the spike
\(T^c\) - Set of support indices **not** expected - sparser than support itself

[Wang, et. al., 2010; Vaswani et. al., 2010, Charbiwala, 2009]
Learning a Union of Supports Results in Very Low Sparsity

Reducing Sparsity Across a Sequence of Spikes

#Spike Occurrences

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

Norm

$10^4$
Learning a Union of Supports Results in Very Low Sparsity

Reducing Sparsity Across a Sequence of Spikes

- Norm of Magnitude Difference
- Norm Outside Previous Spike Support
Learning a Union of Supports Results in Very Low Sparsity

Reducing Sparsity Across a Sequence of Spikes

- Norm of Magnitude Difference
- Norm Outside Previous Spike Support
- Norm Outside Learned Union of Supports
CS Neural Recording Process

In vivo

[Diagram showing the process steps: Amplify and Digitize, Band Pass Filter, Spike Detect and Align, Compressive Sampling, Radio TX]

Ex vivo

[Diagram showing the process steps: Radio RX, CS Recovery, Spike Sorting, Add Support]

In vivo

Out vivo

Diagram showing the process steps: Amplify and Digitize, Band Pass Filter, Spike Detect and Align, Compressive Sampling, Radio TX

Ex vivo

Diagram showing the process steps: Radio RX, CS Recovery, Spike Sorting, Add Support

Diagram showing the process steps: Amplify and Digitize, Band Pass Filter, Spike Detect and Align, Compressive Sampling, Radio TX

Ex vivo

Diagram showing the process steps: Radio RX, CS Recovery, Spike Sorting, Add Support
Learned Union of Support Results

- 22.1 measurements for 20dB SNDR
- 18x → 43x compression
Comparison with Oracle Support Knowledge

![Graph showing SNDR (dB) vs. Number of Measurements/Spike with lines for Oracle Support, Learned Union of Supports, and Conventional Basis Pursuit.](image-url)
Stability of Union Progression
Why Union CS Works

\[ \Delta : \text{Number of False Negatives} \quad \Delta_e : \text{Number of False Positives} \]

\[
\|z - \hat{z}\|_2 \leq \lambda \sqrt{|\Delta|} \sqrt{\frac{\theta^2 |T|,|\Delta|}{(1 - \delta |T|)^2}} + 1 \frac{1}{1 - \delta |\Delta| - \frac{\theta^2 |T|,|\Delta|}{1 - \delta |T|}} + \frac{\|\sigma\|_2}{\sqrt{1 - \delta |N \cup \Delta_e|}} \]  

(4)
Clustering Performance

Original

CS Neural Recording

16 measurements for 90% clustering accuracy
18x → 56x compression
Power Consumption Comparison

![Graph showing power consumption comparison across different spike rates. The x-axis represents spike rate (Hz) on a logarithmic scale, while the y-axis represents average power (μW) also on a logarithmic scale. Different lines represent different data sets: Spike IDs, 21 Spike Features, 12 CS Measurements, 24 CS Measurements, Raw Spikes, and Raw Neural Signal. The graph illustrates how power consumption increases with spike rate for all data sets.]
Conclusions and Future Directions

- 2x compression versus sensing raw spikes at low power
- Sorting possible on compressed version at lower rates
- In development: 8-channel FPGA based implementation
- Within the year: ASIC based 16-channel solution
Thank You!

Slides, Code, Data @
http://nesl.ee.ucla.edu/people/zainul
Backup Slides
Magnitude of Coefficients of Consecutive Spikes are Dissimilar

Spikes differ by 90% on the average in DWT domain.
Magnitude of Mismatched Coefficients in Consecutive Spikes is Lower

Sparsifying a Sequence of Spikes

- Difference between consecutive spikes. Mean=89.4%
- Norm outside support of previous frames. Mean=31.6%

Spikes are 70% sparser outside support of previous spike
Magnitude of Mismatched Coefficients from All Previous Spikes is Very Low

Sparsifying a Sequence of Spikes

- Difference between consecutive spikes. Mean=89.4%
- Norm outside support of previous frames. Mean=31.6%
- Norm outside union of support of all previous frames. Mean=6.5%

Spikes are 95% sparser outside support of all previous spikes
Comparison with Modified-CS

![Graph showing SNDR (dB) vs. Number of Measurements / Spike for different methods: Oracle Support, Learned Union of Supports, Modified CS, and Conventional Basis Pursuit.](image)
Sorting Performance with Modified-CS

![Graph showing classification accuracy vs. number of measurements per spike for different methods: Oracle Support, Learned Union of Supports, Modified CS, and Conventional Basis Pursuit. The graph illustrates how the classification accuracy improves as the number of measurements increases, with each method showing distinct performance characteristics.]