



Spike sorting based on noise-assisted semi-supervised learning methodologies

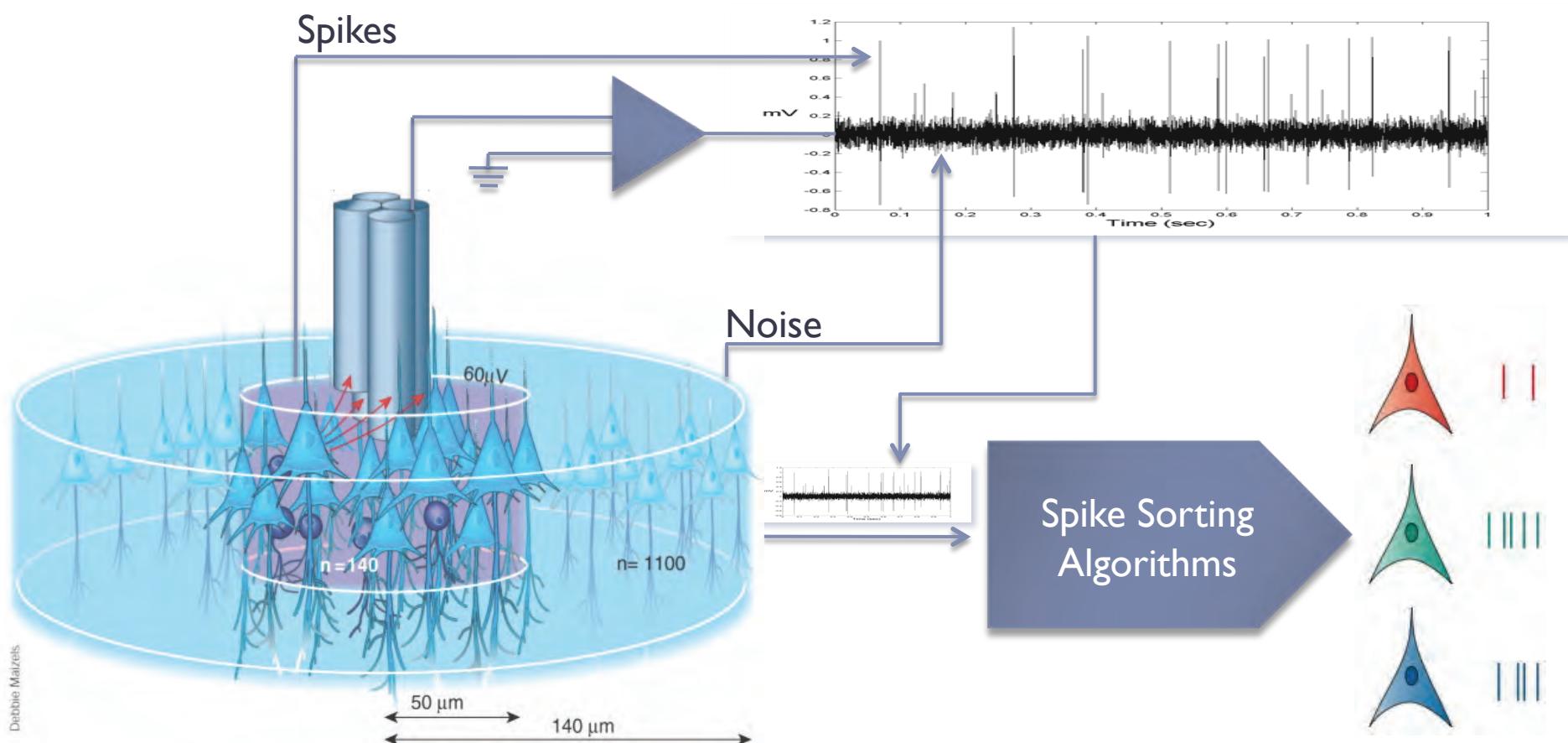


Dimitrios A. Adamos PhD



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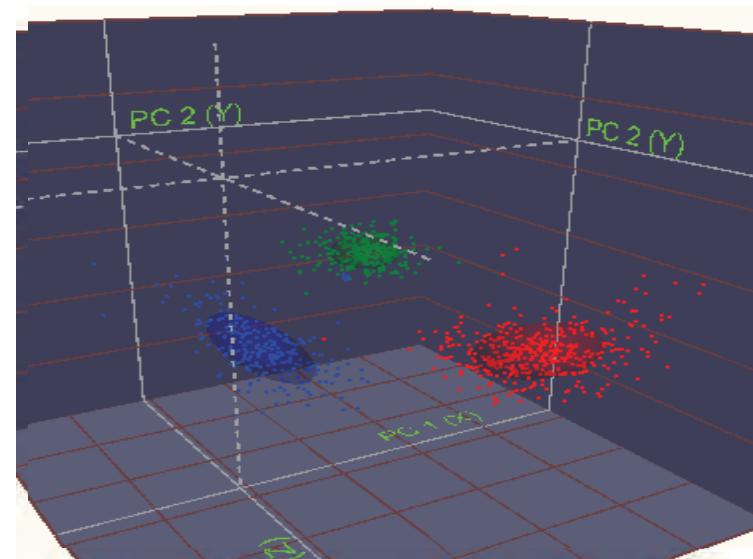
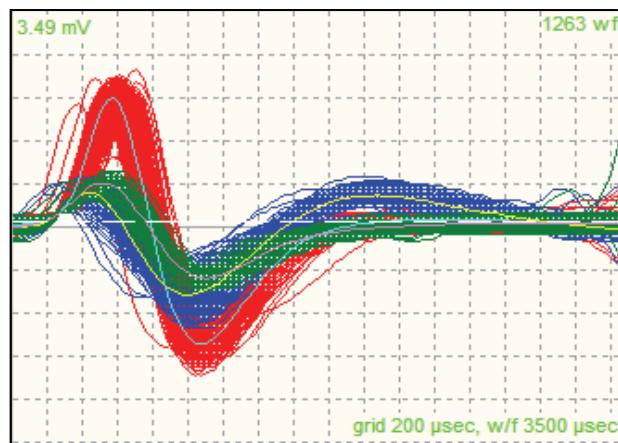
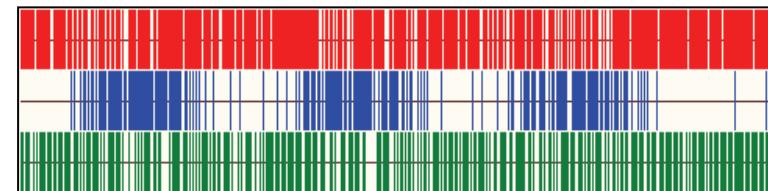
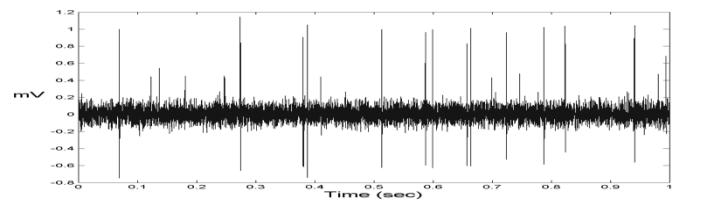
Extracellular recordings



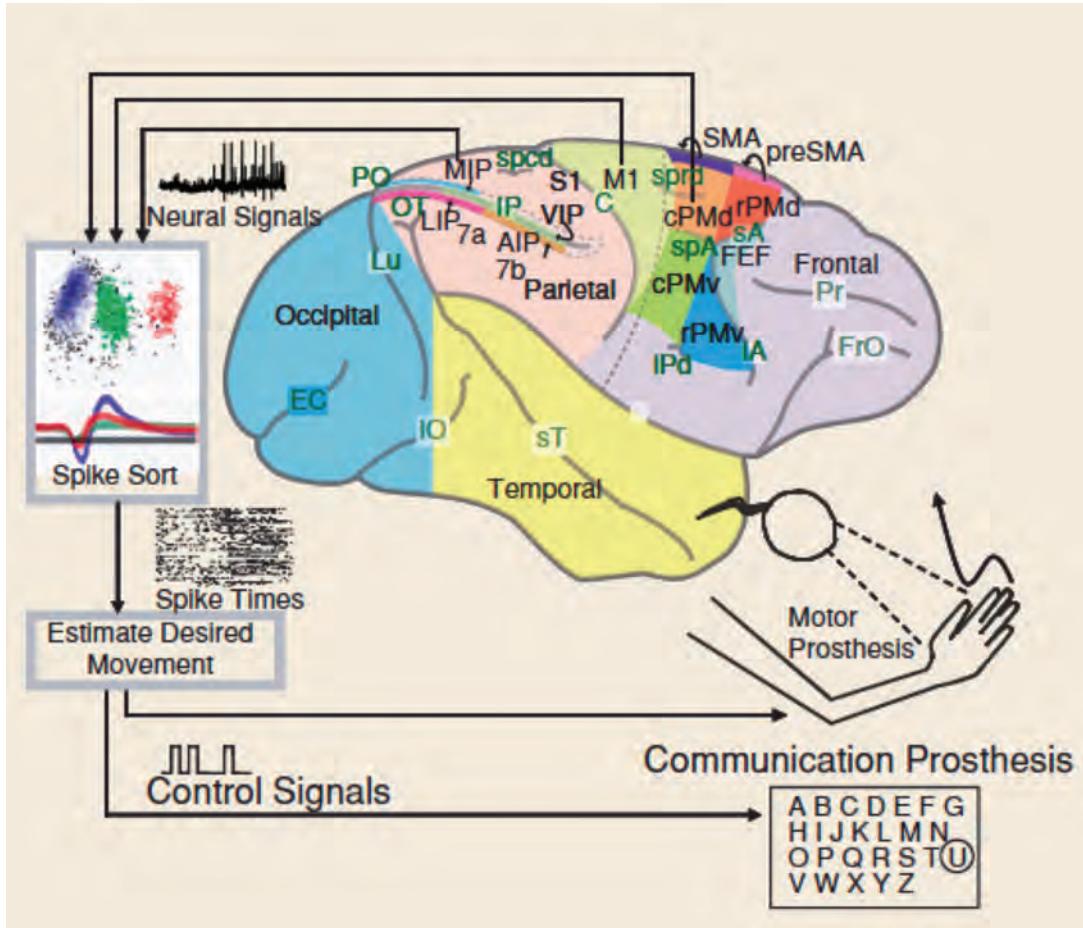
Buzsáki, G. (2004). Large-scale recording of neuronal ensembles. **Nature Neuroscience**



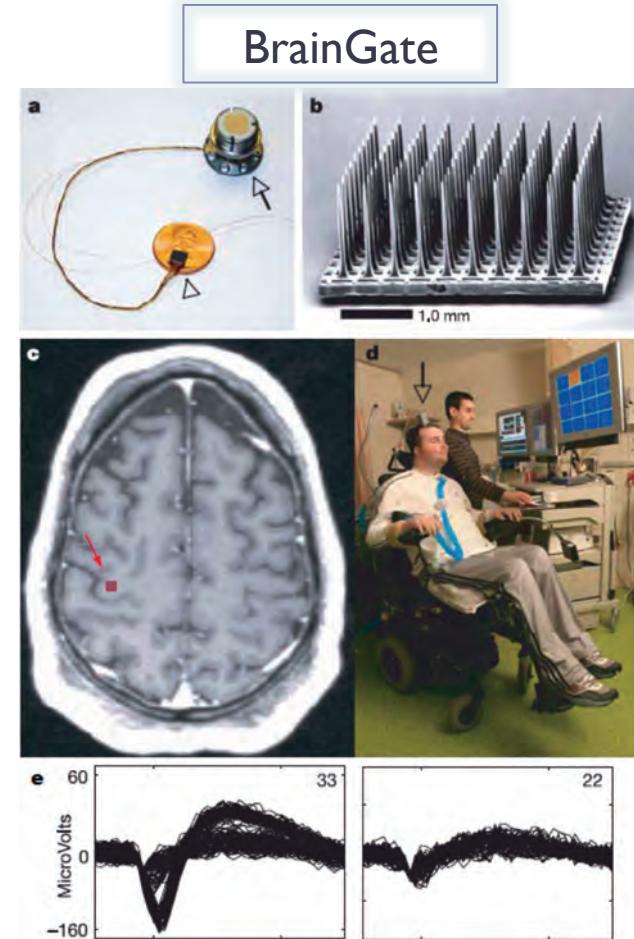
Spike sorting in a nutshell



Spike sorting applications #1



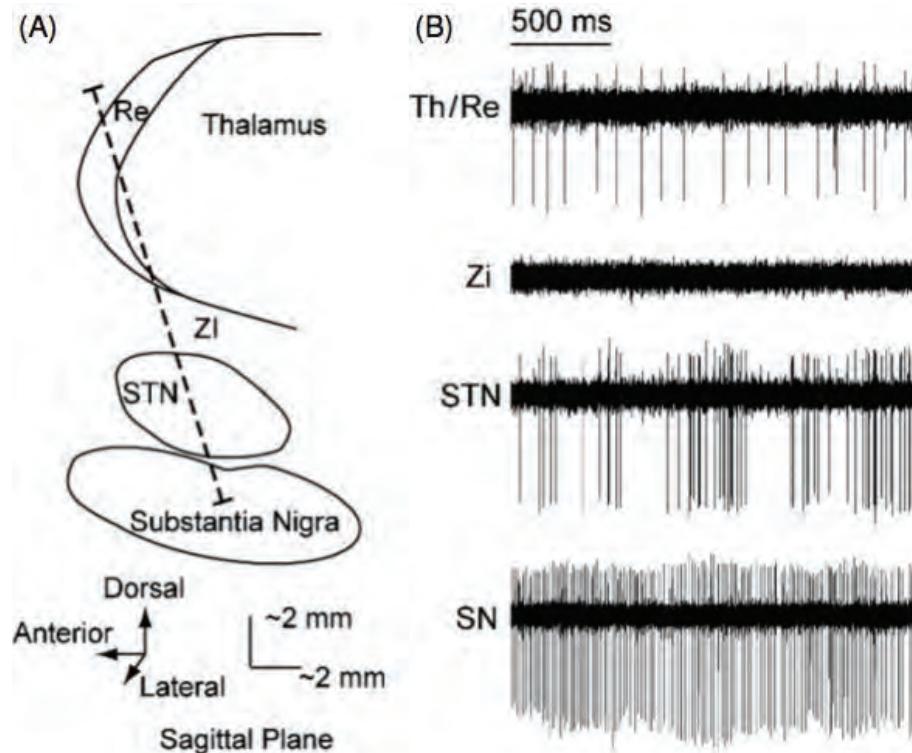
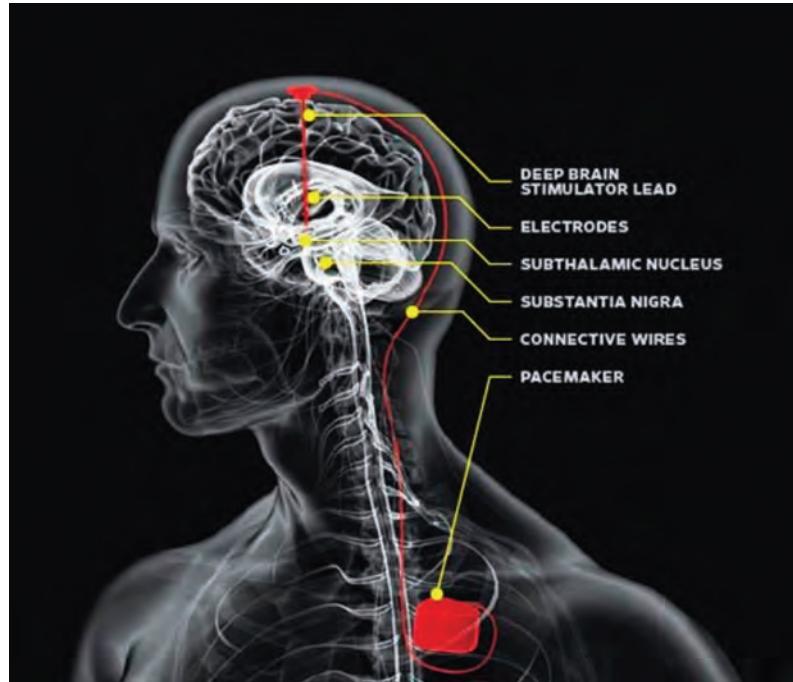
Linderman et al. (2008). Signal processing challenges for neural prostheses. *IEEE Signal Processing Magazine*



Hochberg et al. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature*



Spike sorting applications #2



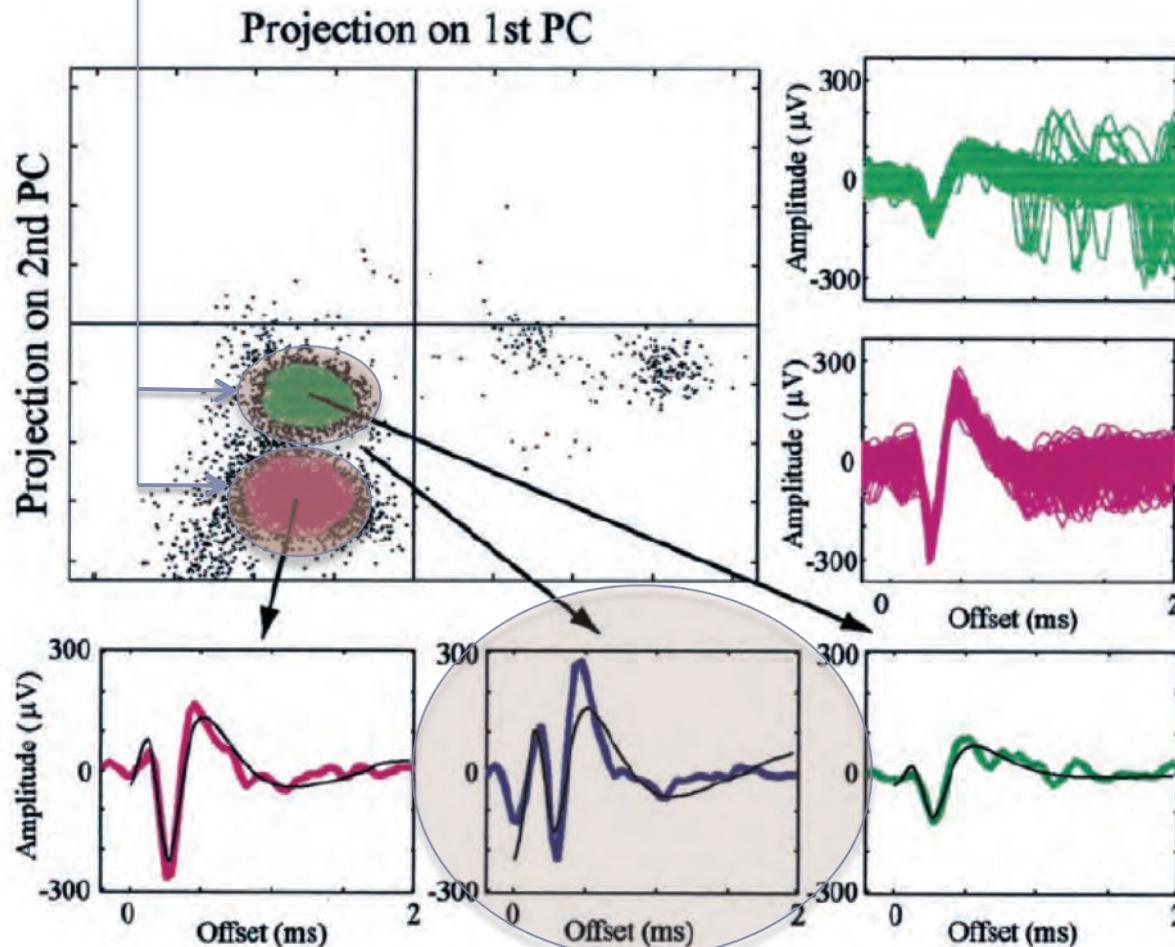
- ▶ Functional STN Targeting during DBS surgery

Wong et al. (2009). *Functional localization and visualization of the STN from microelectrode recordings acquired during DBS surgery with unsupervised machine learning*. **J Neural Eng**



Challenges in Spike sorting

- ▶ Clustering | Correct estimation of active neurons
- ▶ Overlapping spikes



Spike sorting of spikes from two neurons recorded on a single electrode

Bar-Gad et al. (2003). Functional correlations between neighboring neurons in the primate globus pallidus are weak or nonexistent. *J Neurosci*

Bar-Gad et al. (2001). Failure in identification of overlapping spikes from multiple neuron activity causes artificial correlations. *J Neurosci Methods*



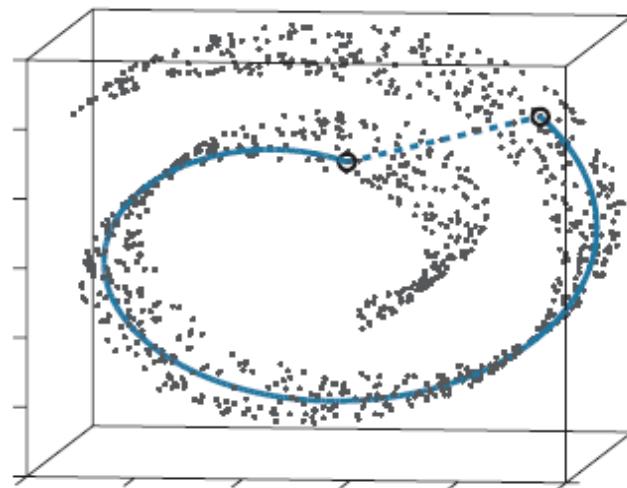
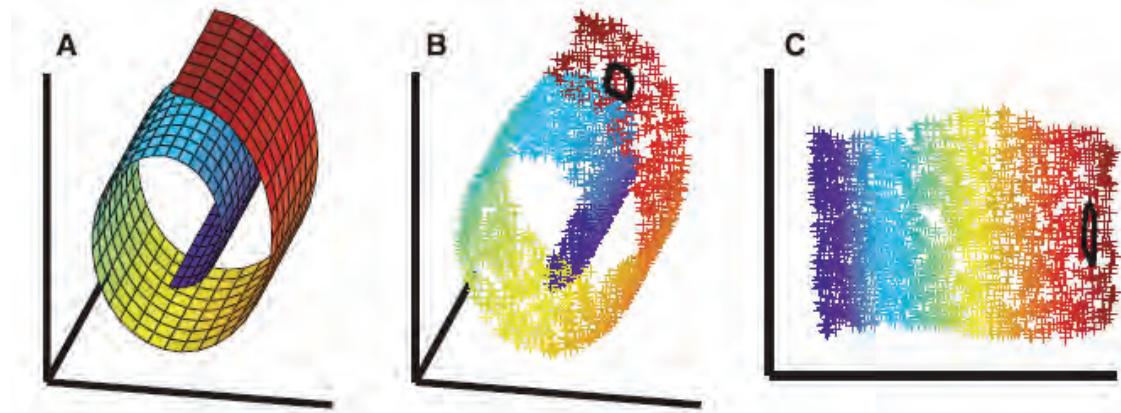
Identifying overlaps: the NASS algorithm

- ▶ Adamos DA, Laskaris NA , Kosmidis EK and Theophilidis G. **NASS: An empirical approach to Spike Sorting with overlap resolution based on a hybrid Noise-Assisted methodology.** **Journal of Neuroscience Methods** 2010;190(1):129-42



Non-linear low-dimensional representation

- ▶ Manifold learning: Isometric Feature Mapping (ISOMAP)



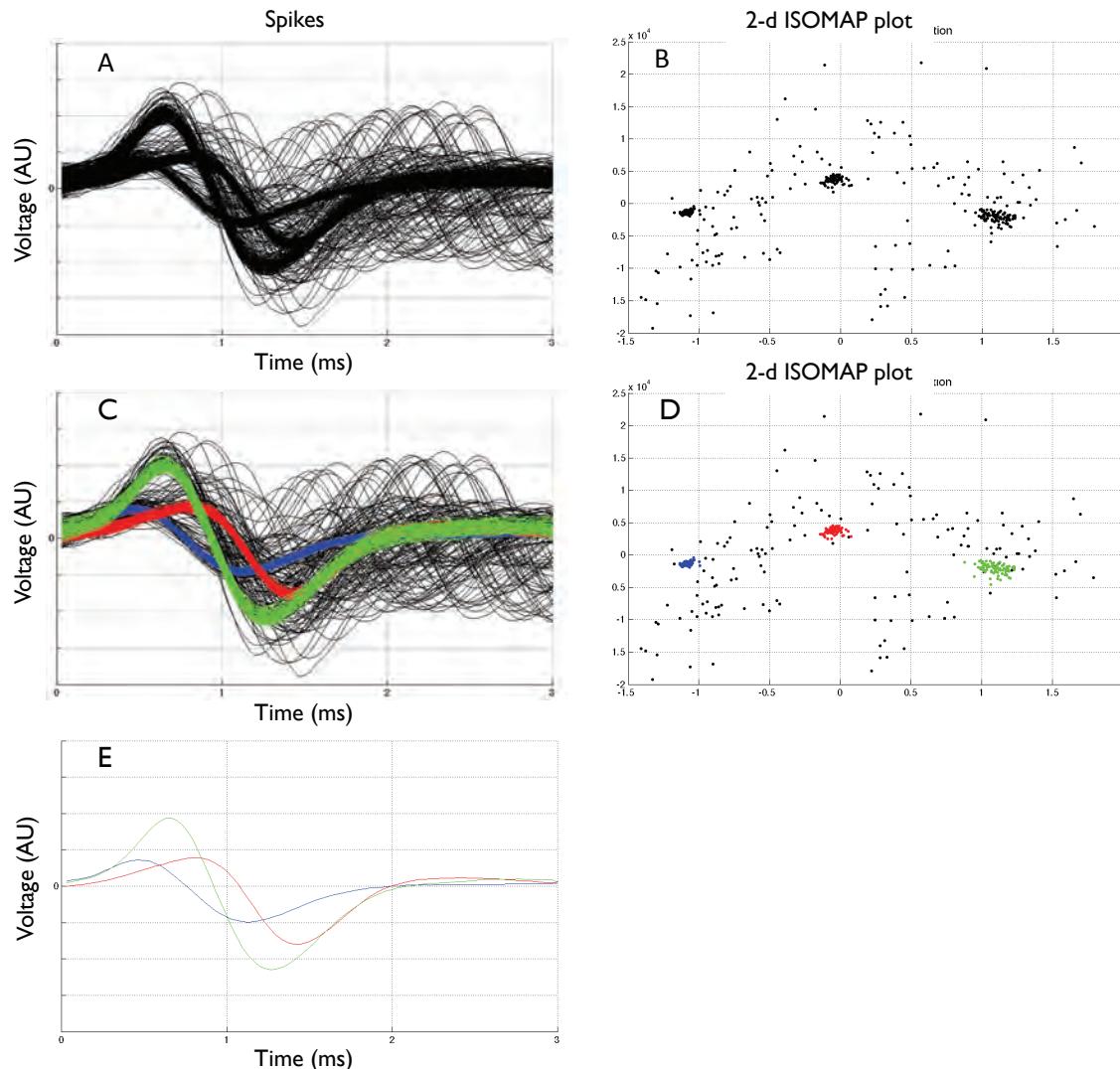
Noise Assisted Spike Sorting (NASS) Algorithm

Low-dimensional ISOMAP representation

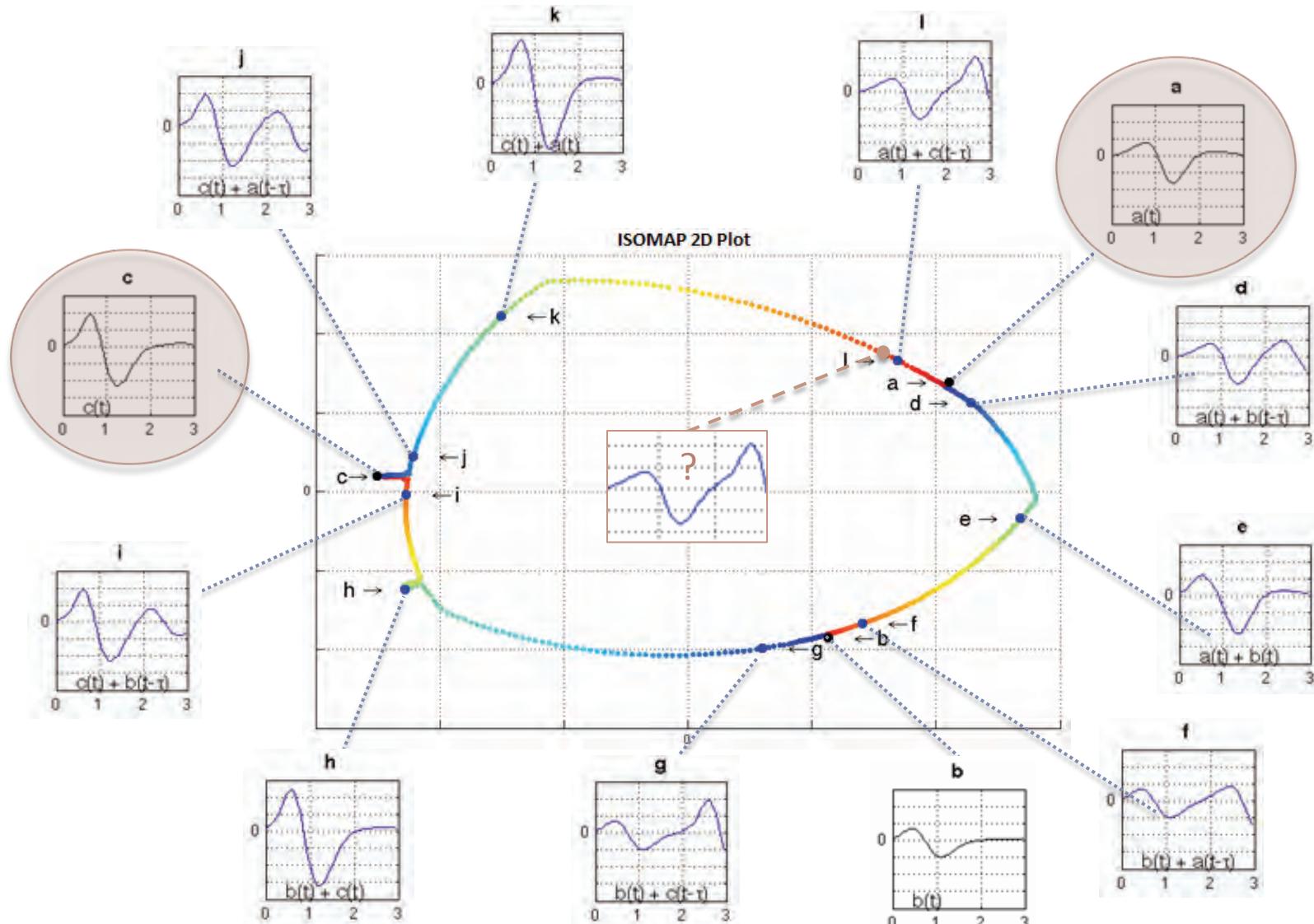
FCM (Fuzzy C-means) clustering

Spikes in black are left **unclassified** for further processing

Spikes in color are used to estimate (using weighted averaging) **prototype waveforms** for each cluster



NASS algorithm: Identifying overlapping spikes



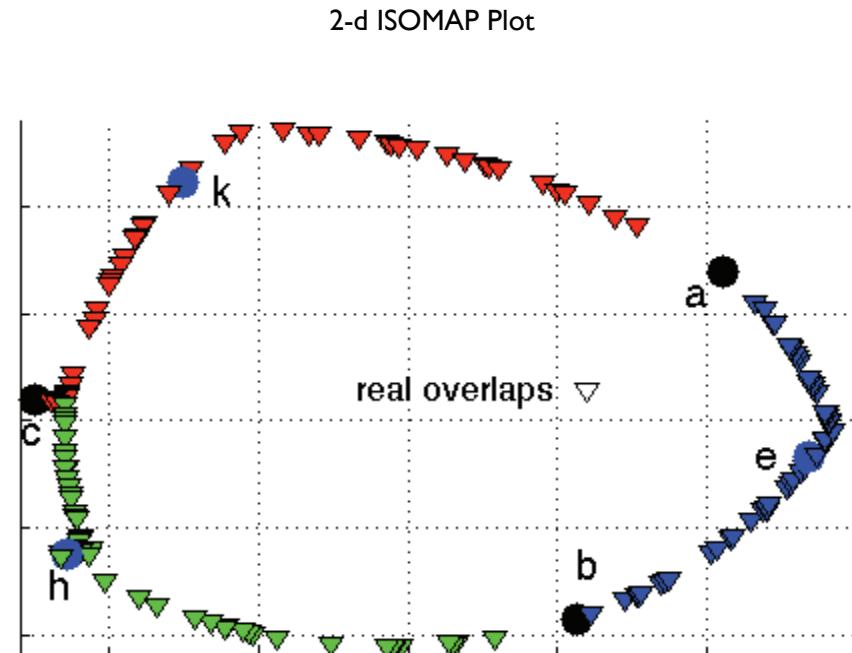
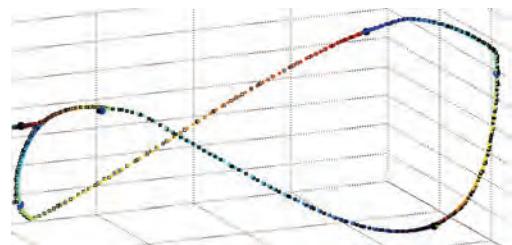
NASS algorithm: Identifying overlapping spikes

Synthetic overlaps and noisy synthetic overlaps are projected to ISOMAP space

Extreme Learning Machine is trained

Real waveforms left unclassified are projected on the same ISOMAP space

The trained Extreme Learning Machine algorithm classifies the real waveforms



Synthetic overlaps



Synthetic 'noisy' overlaps



Real overlaps

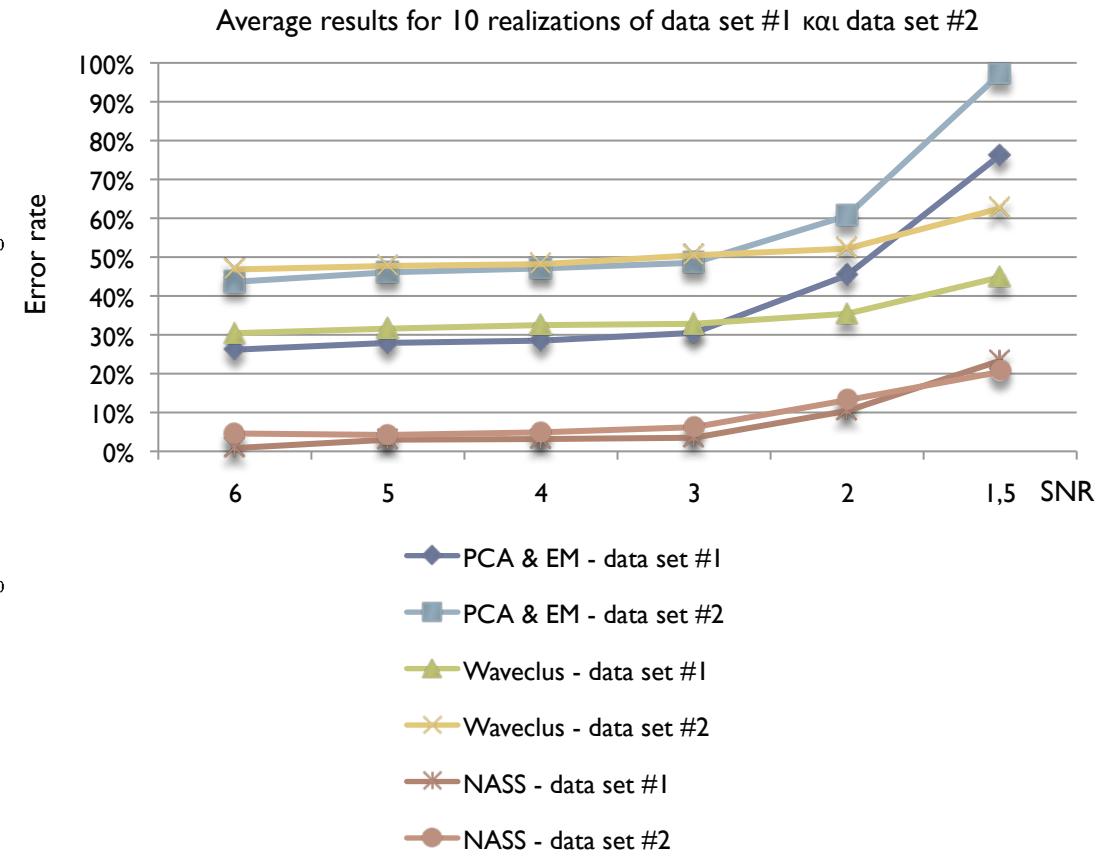
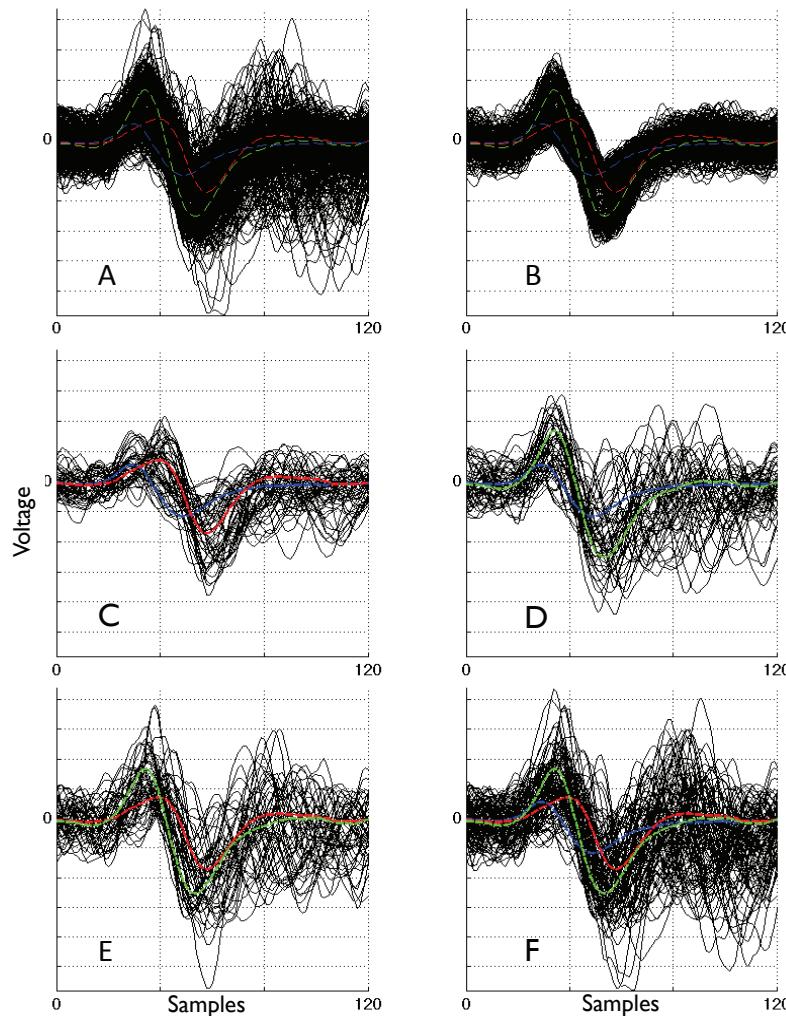


NASS algorithm: Identifying overlapping spikes

► Comparative evaluation using simulated spikes from 3 neurons

- Other methods: [PCA-EM] , [Waveclus*]
- Signal-to-Noise Ratio (SNR) 6 – 1.5

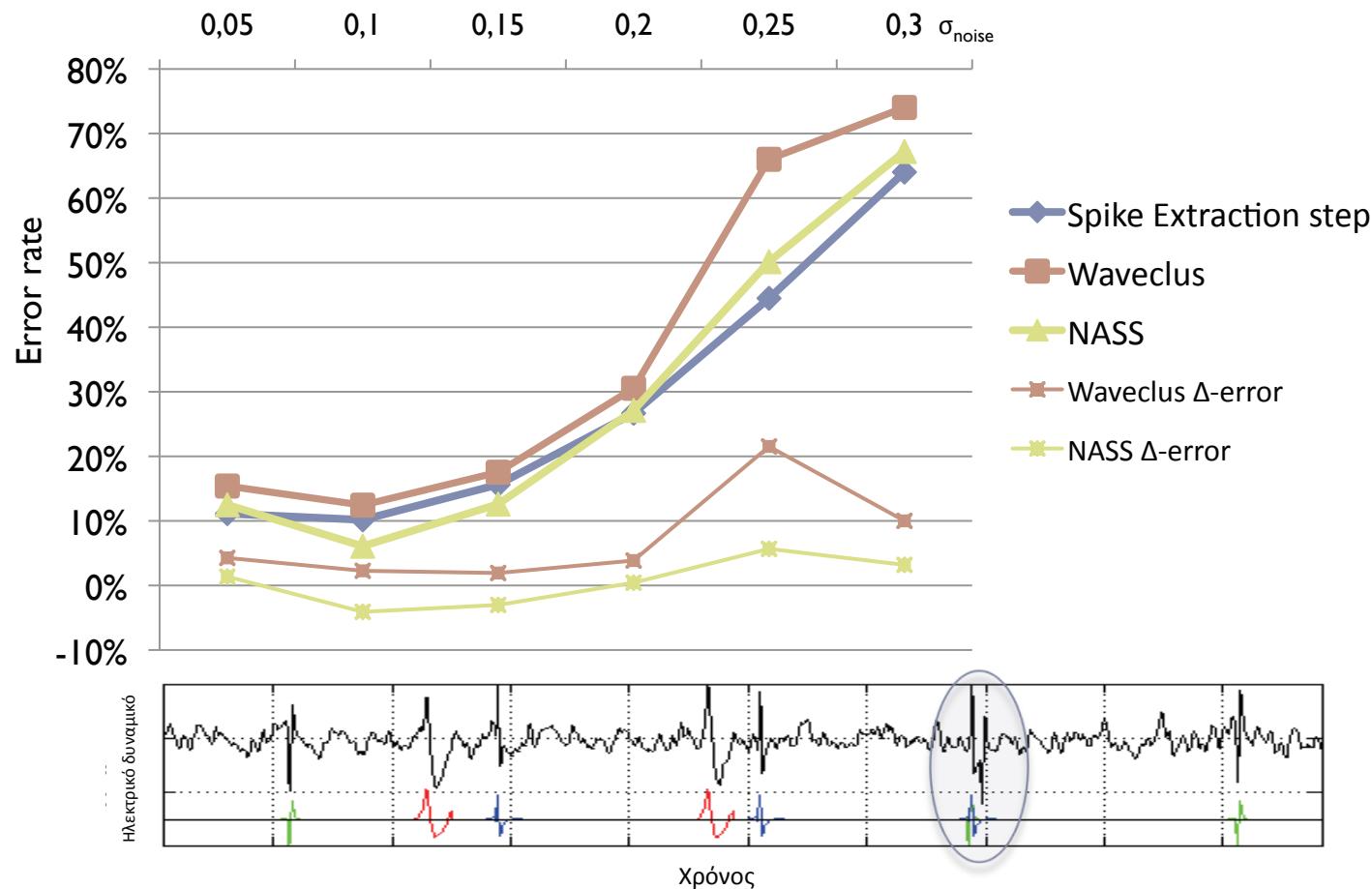
* Quian Quiroga R et al. *Unsupervised spike detection and sorting with wavelets and superparamagnetic clustering*. **Neural Computation**, 2004.



NASS algorithm: Identifying overlapping spikes

Comparative evaluation using simulated neural recordings*, featuring real action potential traces from the cortex and the basal ganglia.

* Quiroga R et al. (2004). *Unsupervised spike detection and sorting with wavelets and superparamagnetic clustering*. **Neural Computation**



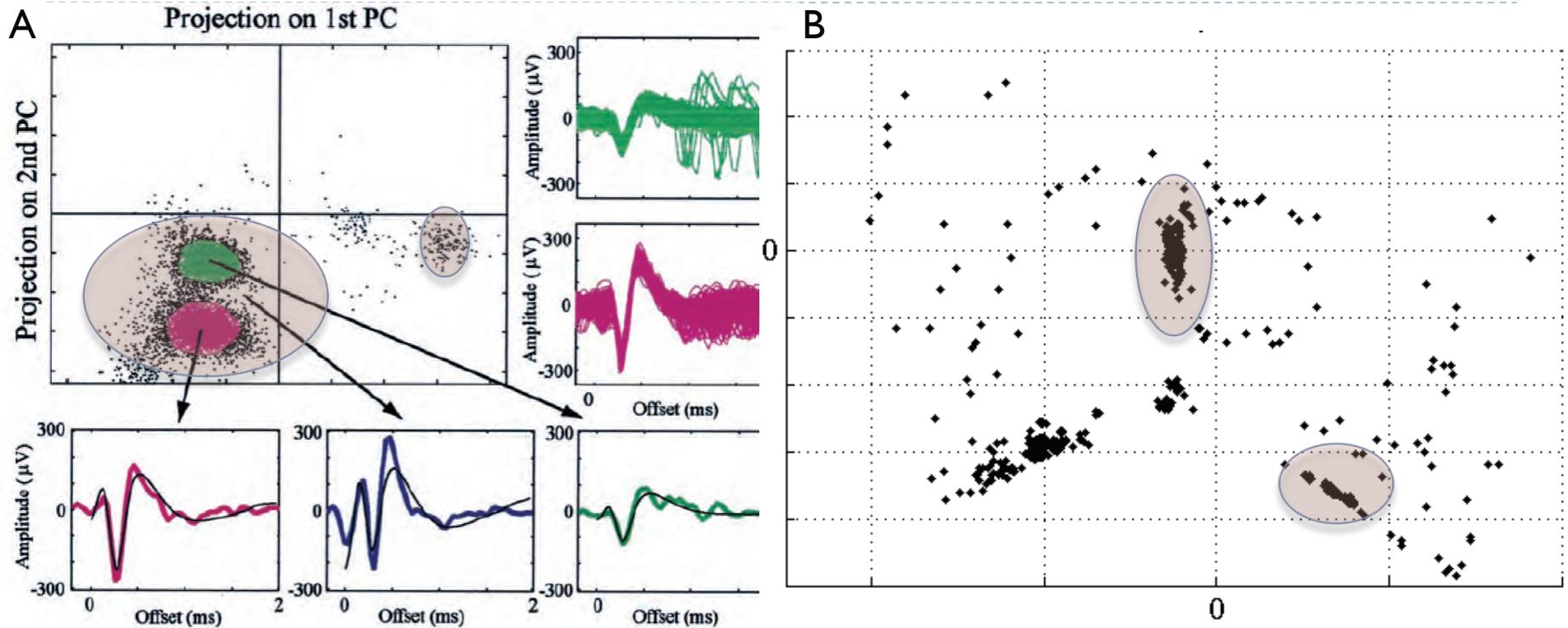
What about clustering?

?



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What about clustering?



- ▶ Background noise cannot be modelled with a stationary Gaussian profile [1 – 2]
- ▶ Gaussianity is not carried over non-linear representations
- ▶ Sparse-firing neurons are usually neglected, as contemporary clustering algorithms target the activity of dominating “hyperactive” neurons.

[1] Fee et al. (1996) Variability of extracellular spike waveforms of cortical neurons, **J Neurophysiol**

[2] Quian Quiroga R et al. (2004). Unsupervised spike detection and sorting with wavelets and superparamagnetic clustering. **Neural Computation**



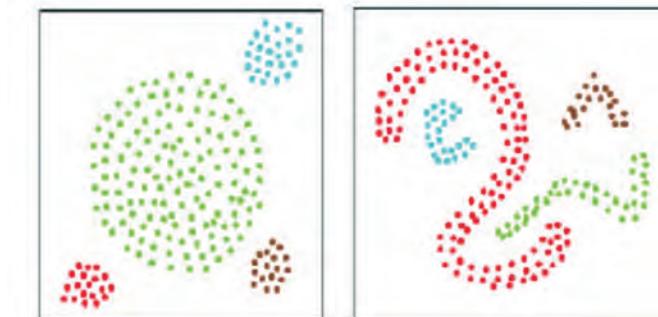
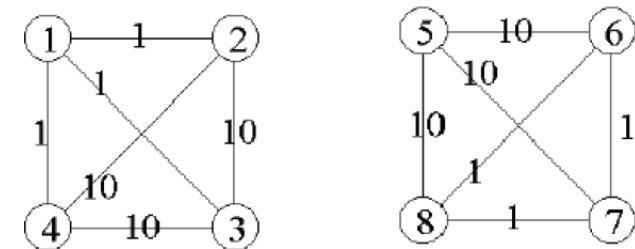
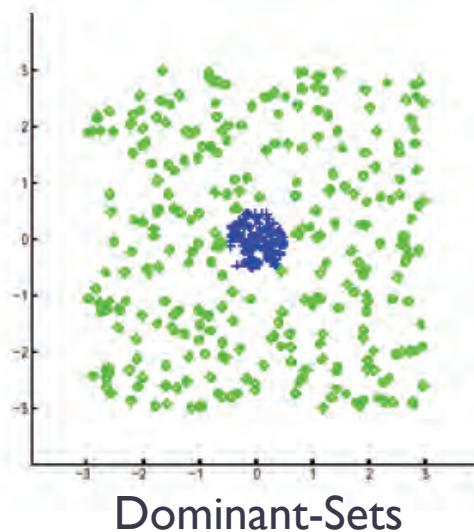
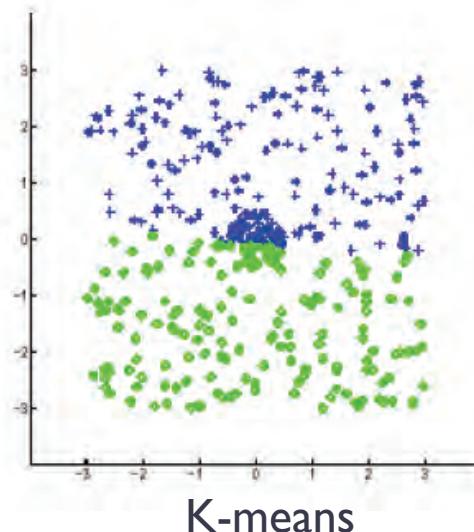
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Methods #2: Graph-Theoretic Clustering

Pavan M and Pelillo M, (2007). Dominant sets and pairwise clustering. **IEEE Transactions on Pattern Analysis and Machine Intelligence**

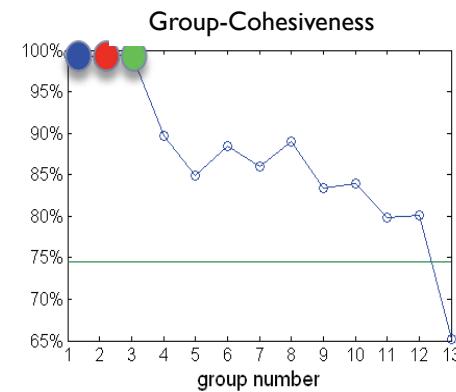
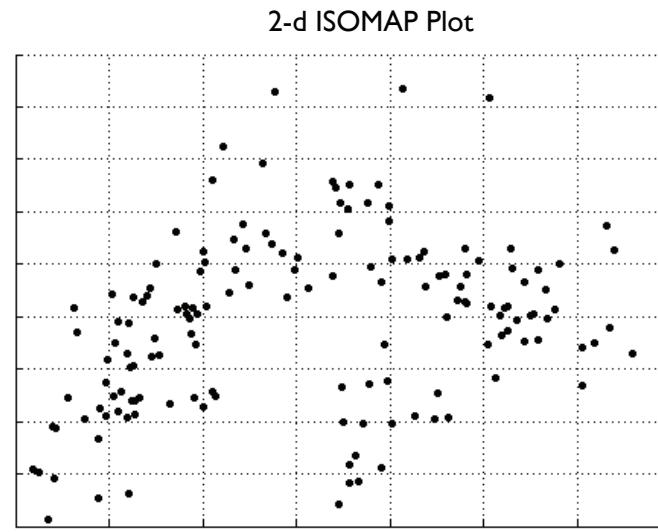
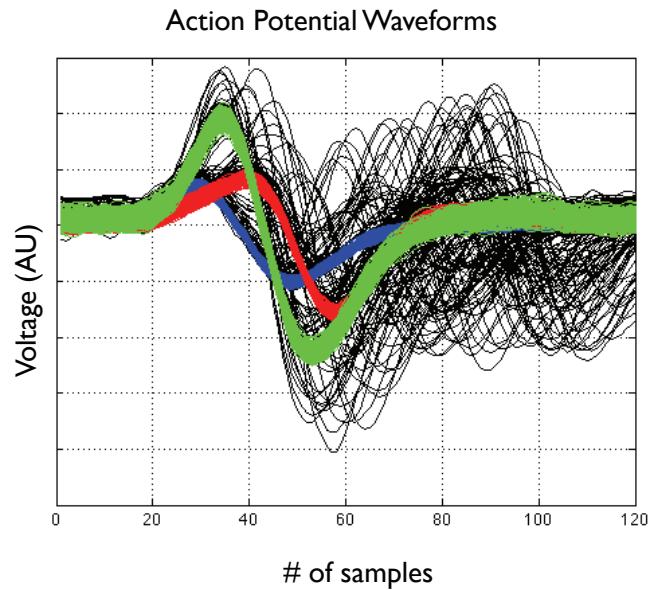
► Dominant-Sets clustering

- ▶ **Internal criterion:** all objects *inside* a cluster should be highly similar to each other
- ▶ **External criterion:** all objects *outside* a cluster should be highly dissimilar to the ones inside
- ▶ **Similarity** is represented by weights:



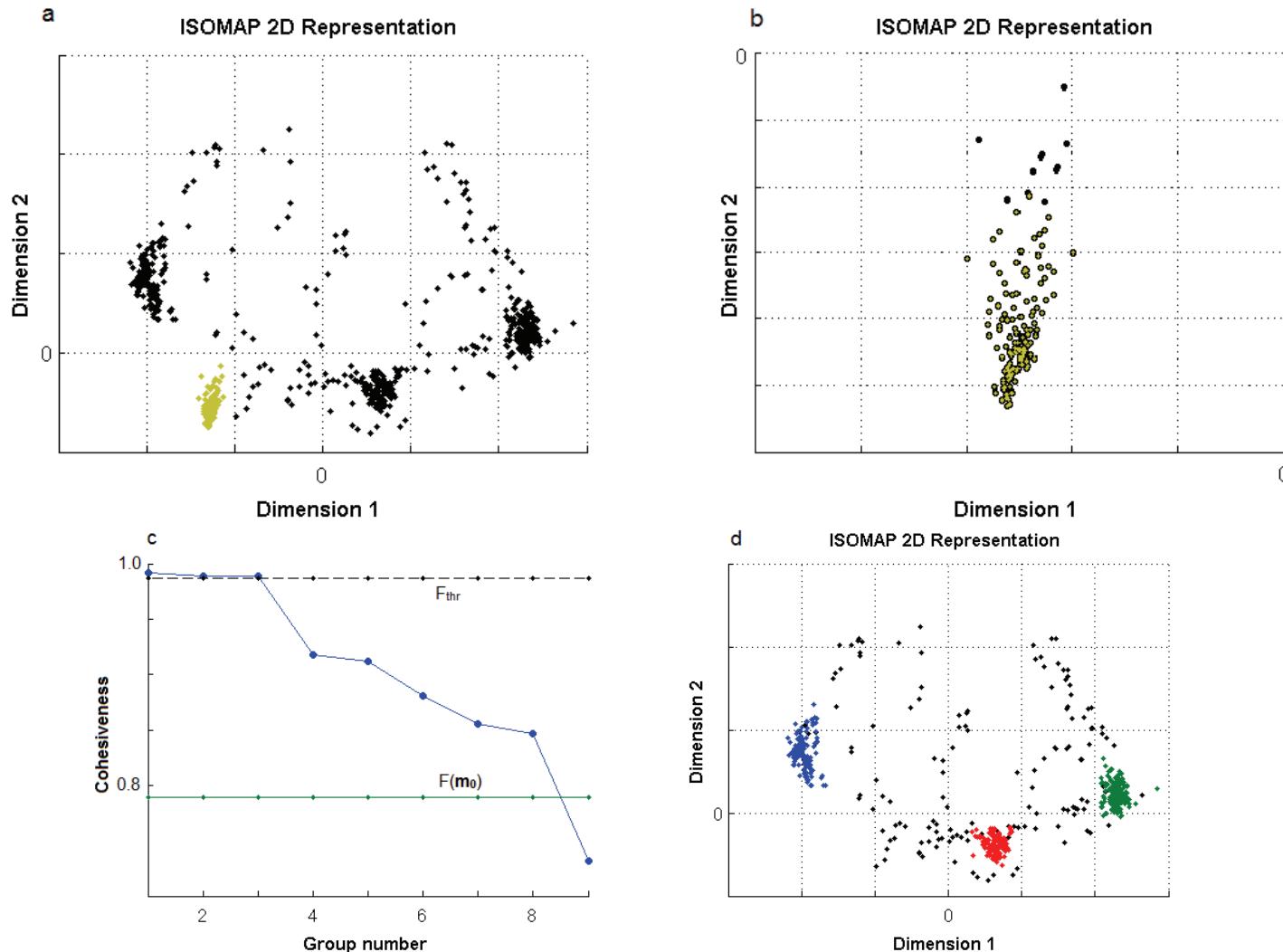
Estimating the number of active neurons

► Replicator Dynamics approach



Estimating the number of active neurons

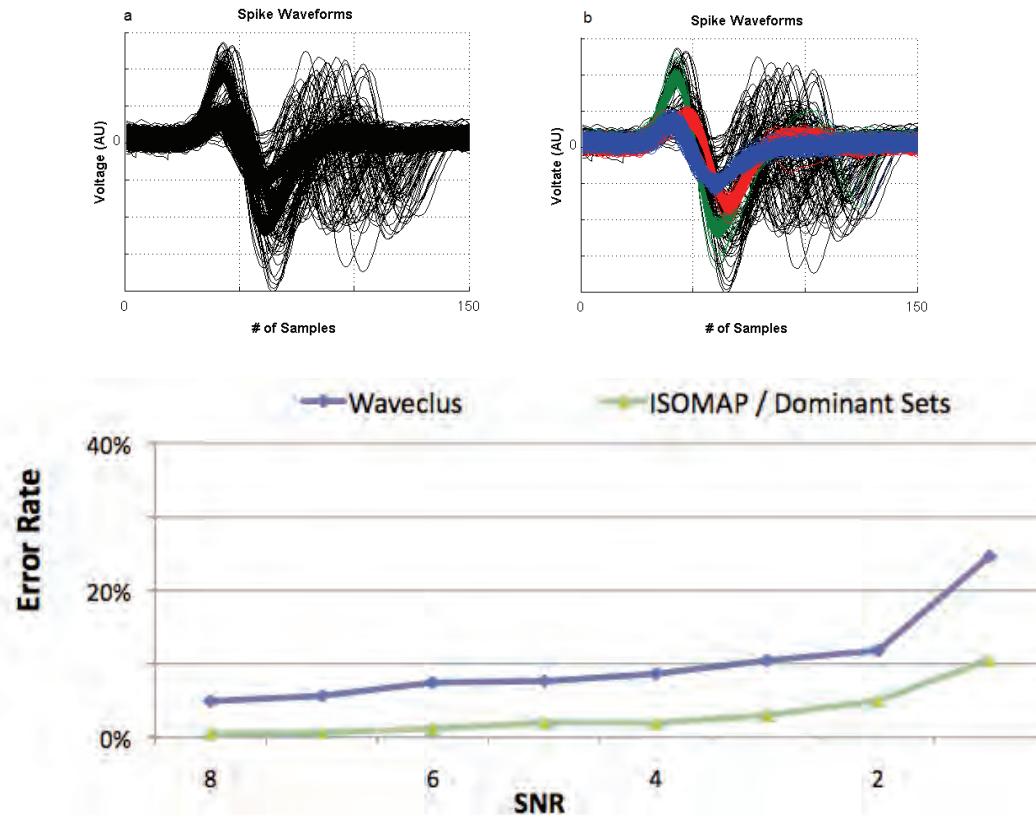
- ▶ Noise-assisted adaptation of the algorithm to the data set



Estimating the number of active neurons

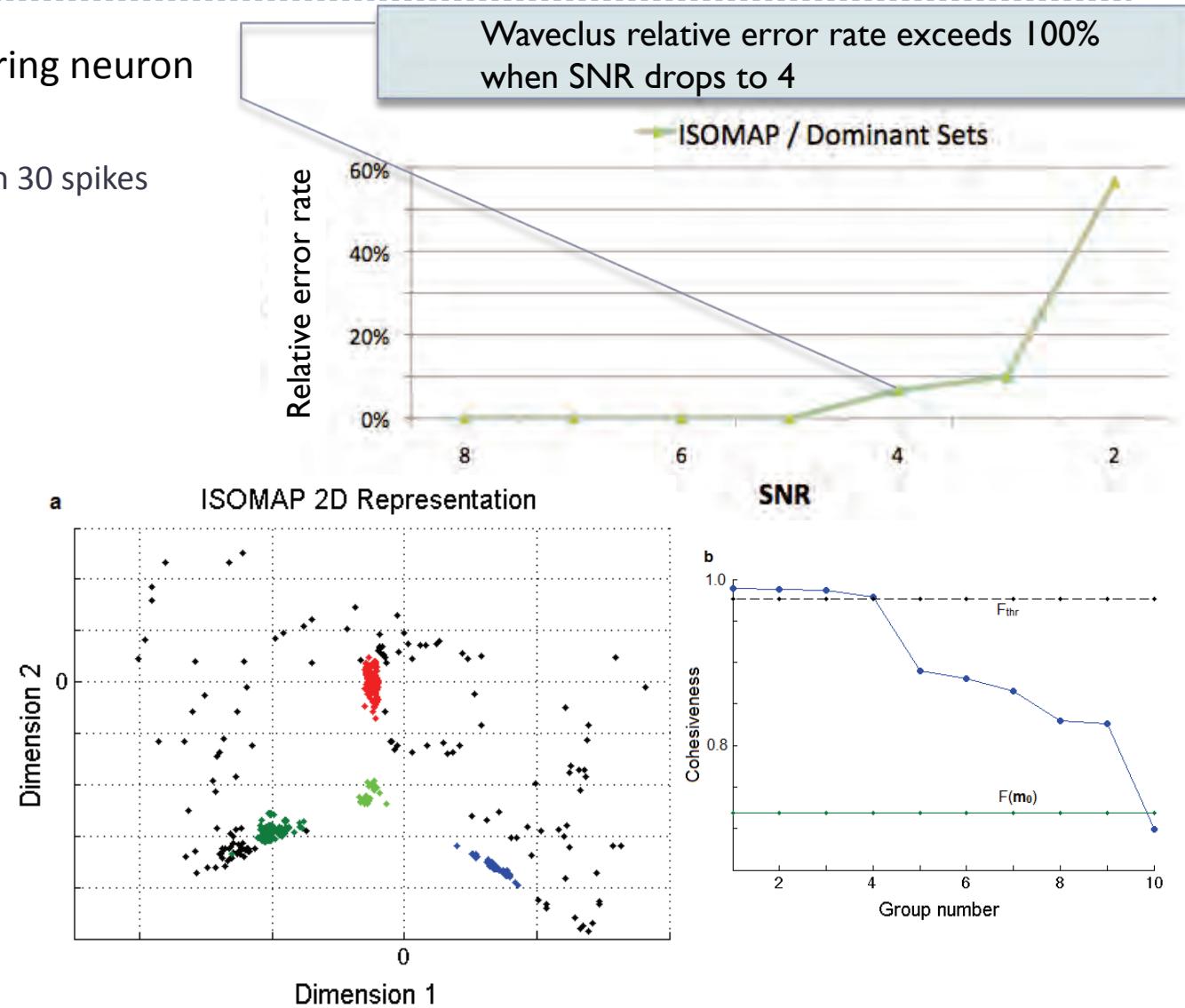
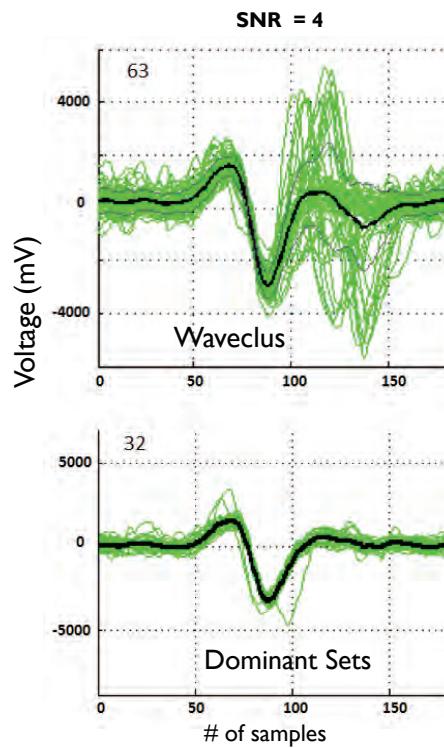
- ▶ Comparative evaluation with Waveclus* for 10 realizations of Data Set #2

* Quiroga R et al. Unsupervised spike detection and sorting with wavelets and superparamagnetic clustering. **Neural Computation**, 2004.



Estimating the number of active neurons

- ▶ Simulating a sparse-firing neuron
 - ▶ Same data set
 - ▶ Additional neuron with 30 spikes



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Neurobot

A COMPUTATIONAL NEUROSCIENCE WEBLOG

26 FEB NASS: an empirical approach to spike sorting with overlap resolution based on a hybrid noise-assisted methodology

Background noise and spike overlap pose problems in contemporary spike-sorting strategies. In this paper, both issues are addressed by a hybrid scheme that combines the robust representation of spike waveforms to facilitate the reliable identification of contributing neurons with efficient data learning to enable the precise decomposition of coactivations.

[Read the rest of this entry...](#)

3 JAN An Expectation-Maximization tutorial in neural signal analysis

In this tutorial by Dr. Liam Paninski, the Expectation-Maximization (EM) algorithm is discussed and illustrated in a variety of neural examples. [Read the rest of this entry...](#)

4 AUG Template matching methods for spike sorting

Template matching is a popular method in spike sorting, mostly employed in the overlap resolution task. Several algorithms have been proposed during the last 5 years, some of them featuring online implementations.

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- » IEEE EMBS: IEEE Engineering In Medicine And Biology Society
- » INCF: International Neuroinformatics Coordinating Facility
- » HSFN: Hellenic Society For Neuroscience
- » The Debian Neuroscience Repository

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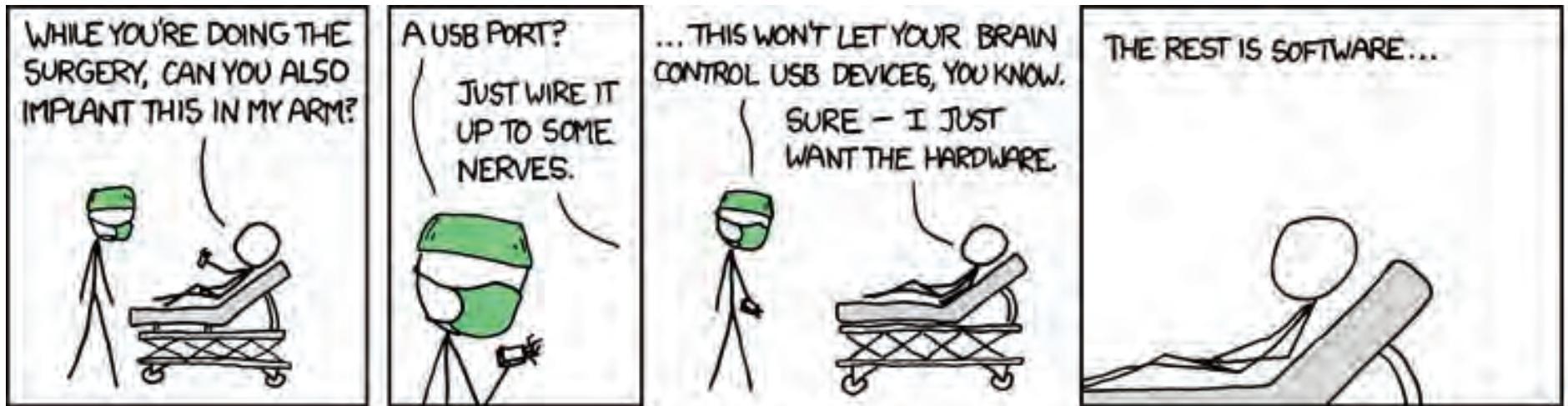
Brain Research
Dimensionality Reduction

Statistical Analysis
Spike Sorting
Information Theory

Conclusions

- ▶ Problem:
 - ▶ Identifying overlapping waveforms
 - ▶ Estimating the number of active neurons
- ▶ Methods
 - ▶ Methods from the graph-theoretic domain
 - ▶ Incorporation of noise in the algorithm adaptation (training) stage
- ▶ Results
 - ▶ Semi-supervised classification of spike overlaps using a bottom-up design approach
 - ▶ Semi-supervised clustering approach with relative ranking of groups
 - High ranking: active neurons, Medium ranking: overlapping and noisy spikes that need further treatment, low ranking: background noise
- ▶ Future
 - ▶ Incorporation of both approaches in a single algorithm





Thank you

