

cck

Borges. Ficciones de un Tiempo Infinito
Artes Visuales /
Ciclo de Charlas y Conferencias

Borges y la Memoria (parte I - Funes el Memorioso)

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Jueves 4 de agosto, 18.30h - Auditorio 513

Neurociencia de Sistemas

- Clase 1. Introducción
- Clase 2. Registros extracelulares y Spike sorting.
- Clase 3. Procesado de información visual.
- Clase 4. Percepción y memoria.
- Clase 5. Decodificación - Teoría de la información.
- Clase 6. Electroencefalografía - Análisis de tiempo-frecuencia y Wavelets.
- Clase 7. Potenciales evocados - Análisis de ensayo único.
- Clase 8. Dinámica no-lineal - Sincronización.

Extracellular recordings

The image shows a micrograph of a neuron with a glass pipette electrode inserted into its soma. Below the micrograph is a long, narrow extracellular recording trace showing a series of sharp, synchronized spikes.

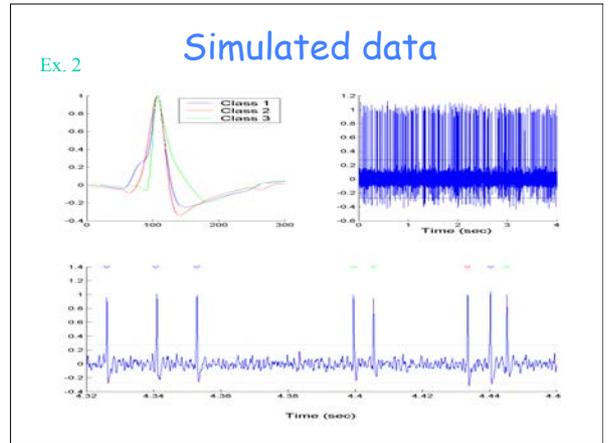
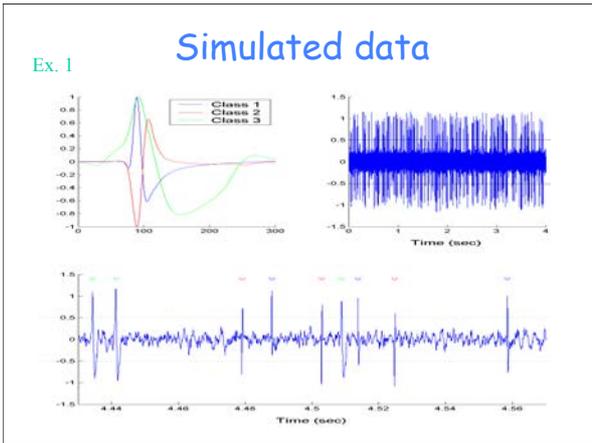
The figure illustrates the process of extracellular recordings. It starts with a diagram of a multi-electrode array (MEA) with a central electrode. To the right, three vertically stacked plots show the signal processing pipeline: 1) 'Local field potential' (raw signal), 2) 'Local field potential' after a 'Low-pass filter', and 3) 'Spikes' after a 'High-pass filter'. Below these are four zoomed-in spike waveforms with their respective spike counts: 16,273 spikes, 269 spikes, 127 spikes, and 42 spikes.

Nature Reviews Neuroscience | 10: 173-185, 2009

Four panels (A, B, C, D) showing extracellular recordings from different electrode sites. Each panel displays a network of neurons with colored spikes and a corresponding extracellular recording trace. Scale bars indicate 20 μm and 4 ms. Voltage scales are provided for each panel: A (100 μV, 50 μV, 20 μV, 10 μV), B (50 μV, 20 μV, 10 μV), C (100 μV, 50 μV, 20 μV, 10 μV), and D (100 μV).

Gold et al 2006

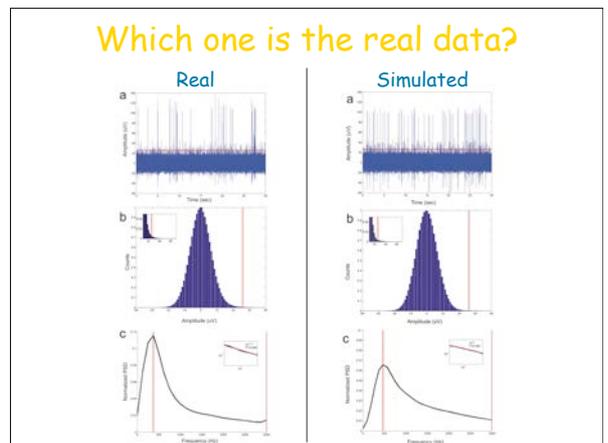
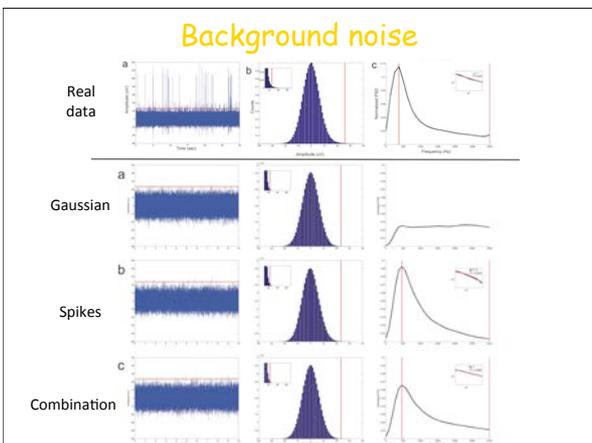
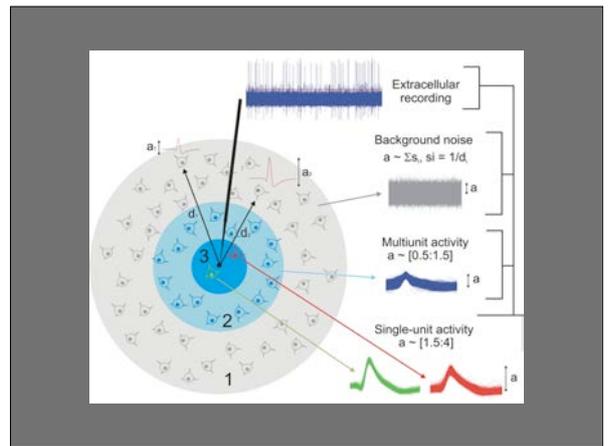
Screenshot of the WaveClust software interface. The main window shows a large extracellular recording trace at the top. Below it are four columns of plots for different clusters: Cluster 1 (blue), Cluster 2 (red), Cluster 3 (green), and Cluster 4 (cyan). Each column contains a 'Spike sorting' plot, a 'Local field potential' plot, and a 'Histogram' plot. The interface includes various control buttons and a 'WaveClust' logo in the top right corner.



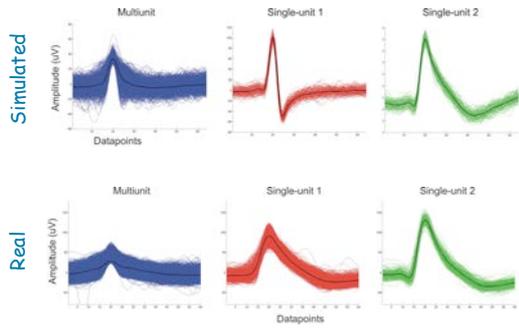
Simulation of extracellular recordings



Juan Martínez Gómez
Martínez et al. J. Neuroscience methods, 2009



Results



A more detailed model...



Luis Camuñas Mesa
Neural Computation, 2013

www.le.ac.uk/csn/neurocube

Generation of extracellular potentials

- Dendritic surface ten to twenty times that of the soma
- Only a small portion of the current flows across the soma
- The neuron branching has an effect on the extracellular potential

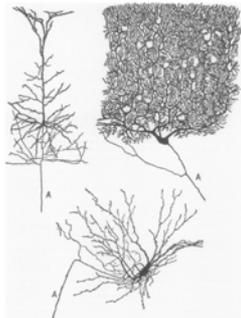
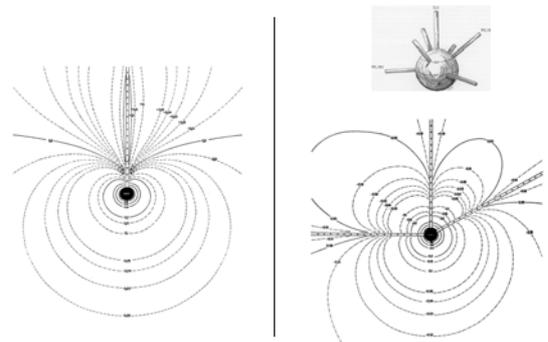


Figure 1 Possible set of extracellular waves (upper left). Possible set of extracellular waves (lower left) illustrating the effect of branching on the extracellular wave. A indicates the soma, which is not all. These illustrations are simplified and only rough approximations from the classic work of Rall (1962).

Rall 1962

Distribution of extracellular potential



Rall 1962

Line source approximation

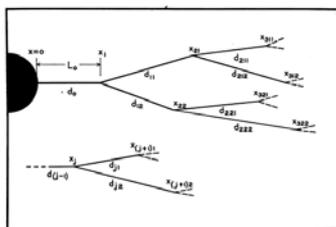
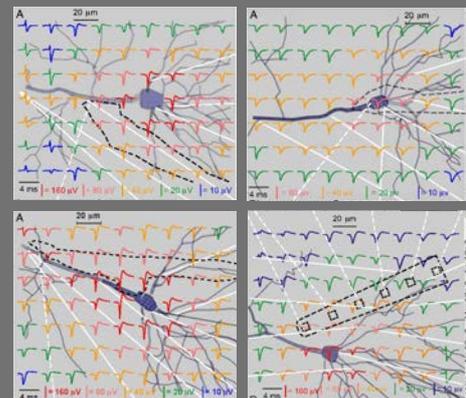
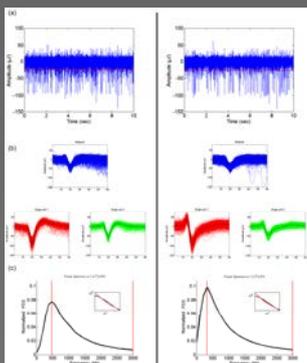
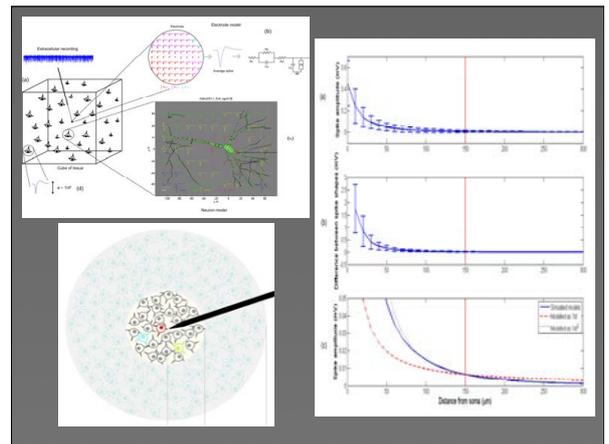
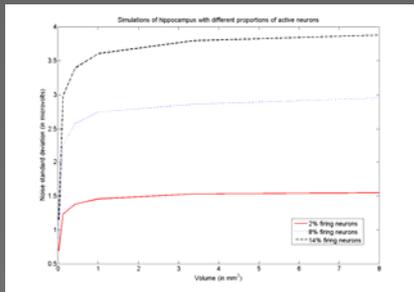
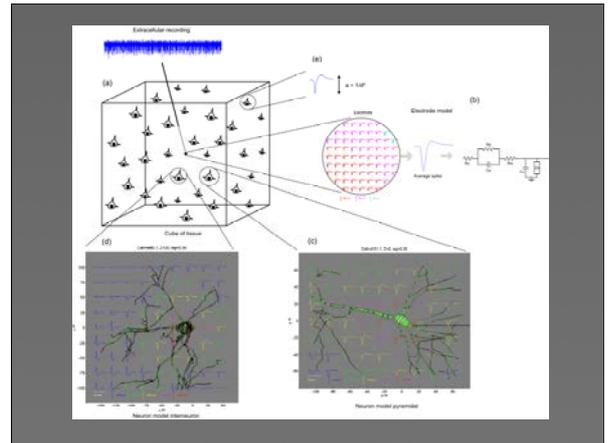
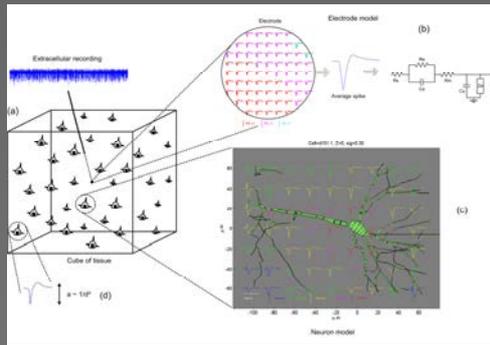


FIGURE 3.A. Dendritic branching diagrams to illustrate the subscript notation used in the treatment of arbitrary branching patterns (see, Rall, 1959).

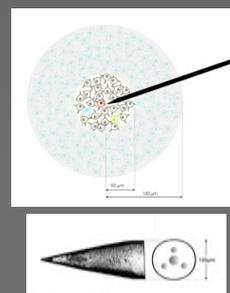


Gold et al 2006

NeuroCube

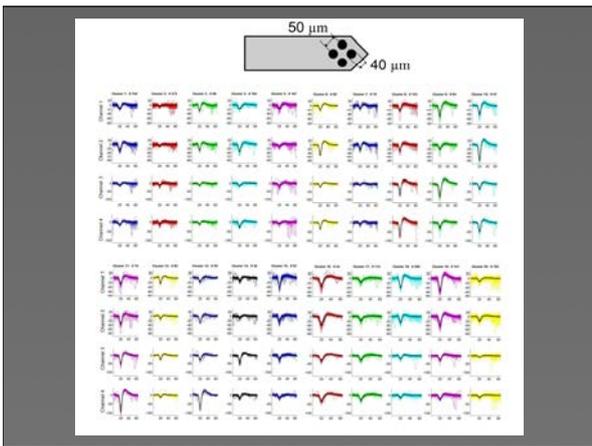
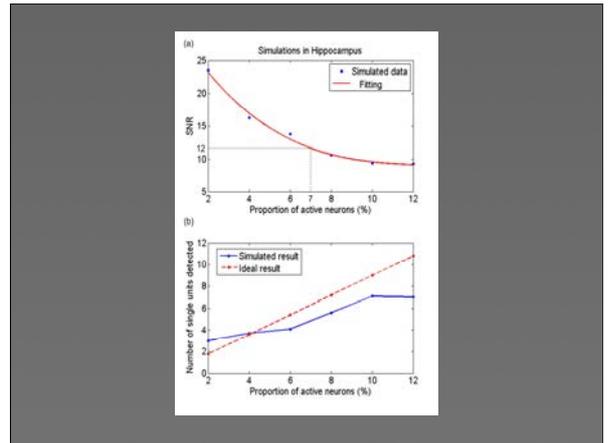
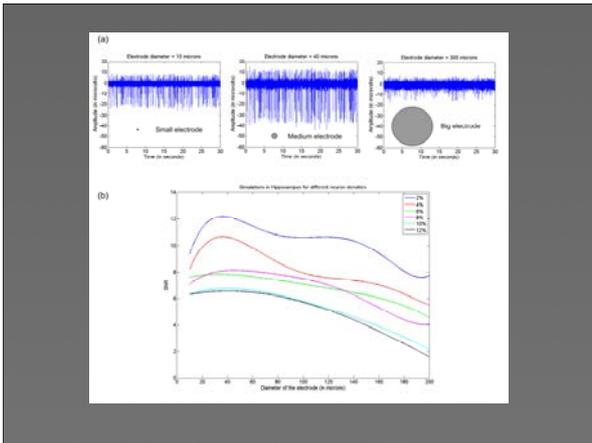


Electrode design

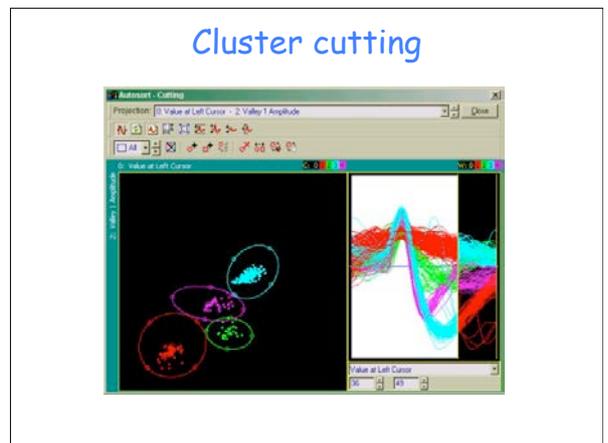
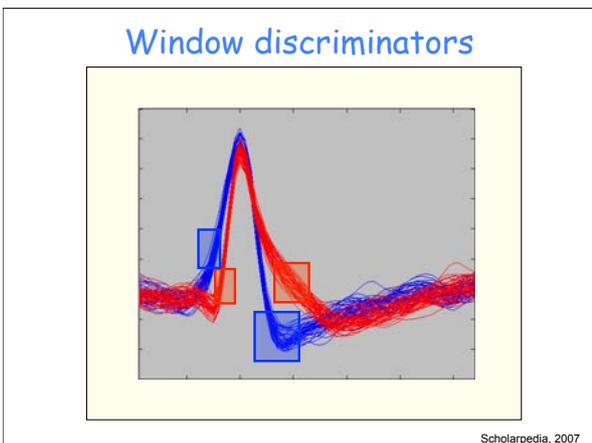


"Despite this prevalence [of the use of microelectrodes for single cell recordings] there remains a good deal of mystery about how best to make these electrodes and how to interpret the extracellular potentials that they record. The attitude of many practical users is the sensibly pragmatic one of the biological assay. When one finds some method of making microelectrodes that successfully isolate units in a given neuronal structure, one 'freezes the design' and attends to the more important task of collecting neural data"

D. Robinson, 1968



Spike sorting



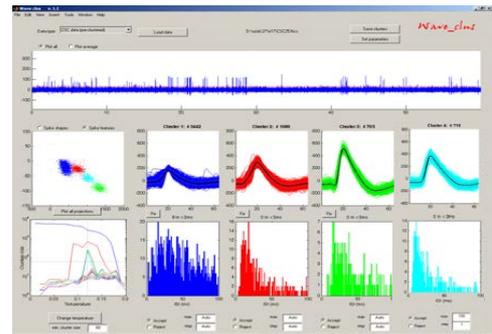
Disadvantages:

- Supervised
 - not practical for many channels, may need readjustment
- Hard to set if spike shapes overlap
- May miss sparsely firing neurons

Our goal

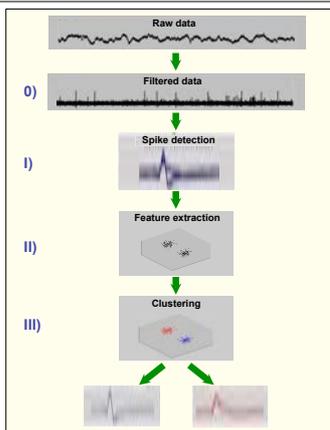
- Algorithm for **automatic** detection and sorting.
- Relatively fast.
- Improve both detection and sorting in comparison with previous approaches.

Wave_clus



www.le.ac.uk/csn

Neural Computation 2004

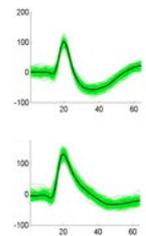


Neural Computation 2004
Scholarpedia 2007
Nat. Rev. Neurosci 2009
Current Biology 2012

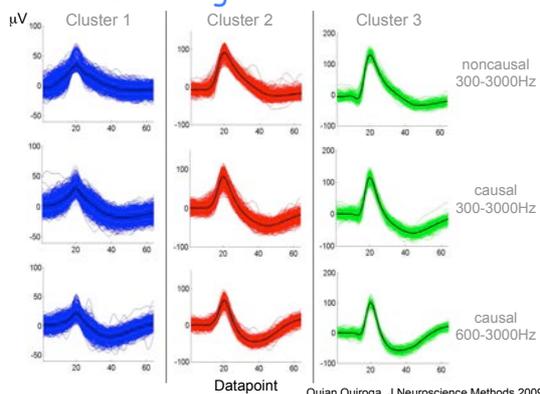
0 - Filtering

- Use of offline noncausal filters

No phase distortions!

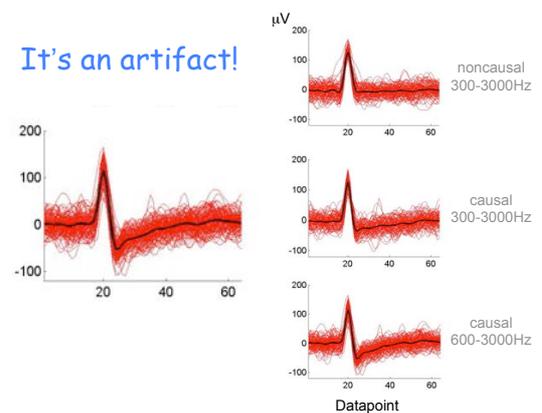


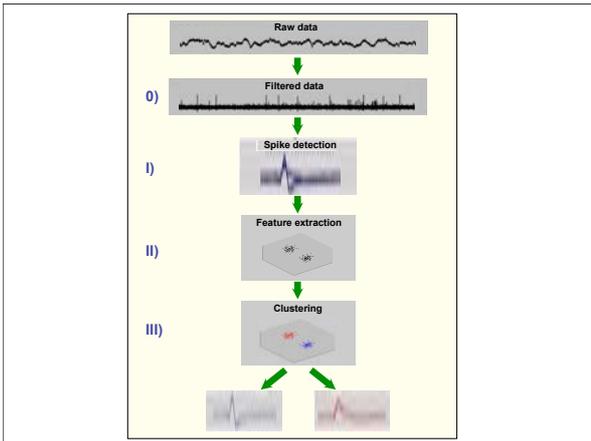
Filtering distortions



Quijano Quiroga, J. Neuroscience Methods 2009

It's an artifact!



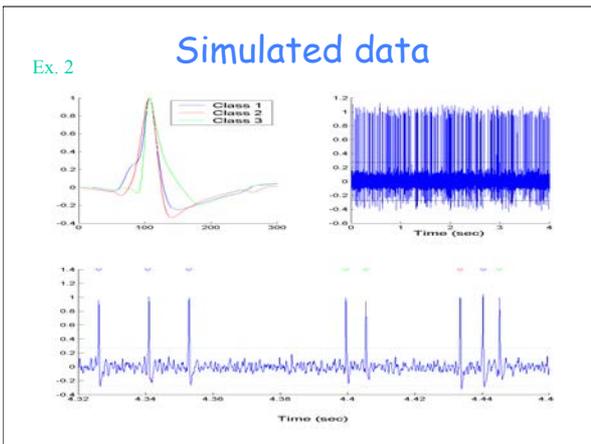


I - Spike detection

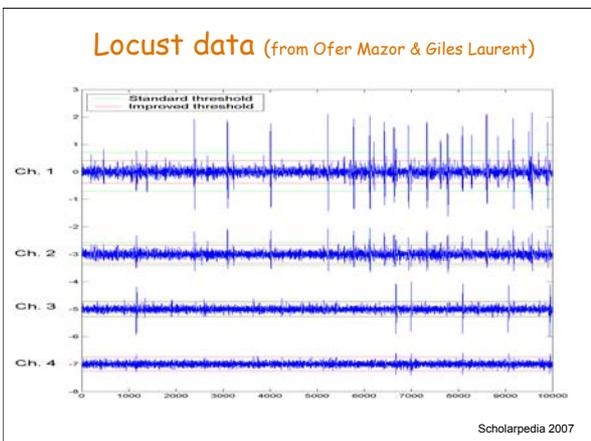
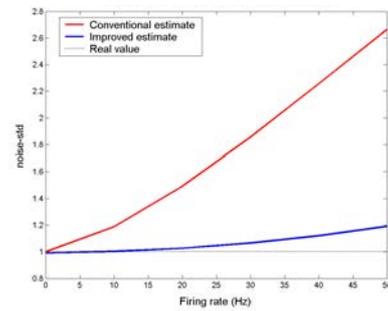
- Set an automatic amplitude threshold

$$T = 4 \cdot \text{median} \left\{ \frac{|x|}{0.6745} \right\}$$

- Spikes are aligned after interpolation with cubic splines.

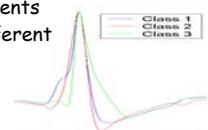


Std estimation

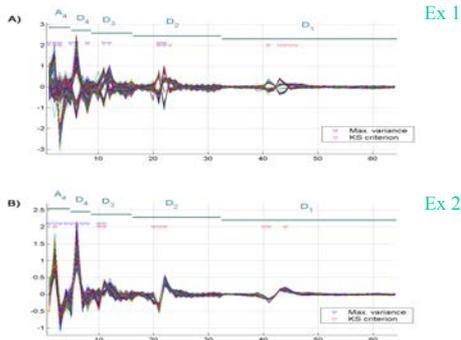


II - Feature extraction: wavelets

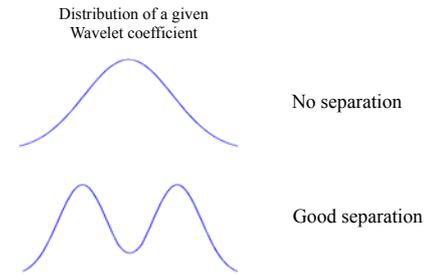
- **Wavelet Transform:** is a time-frequency decomposition of the signal with optimal resolution both in time and frequency.
- **Key idea:** a few wavelet coefficients will be able to separate the different spike classes.



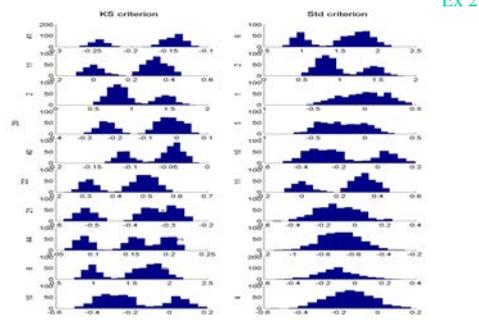
Wavelet coefficients



II a - Selection of wavelet coefficients: KS test of Normality



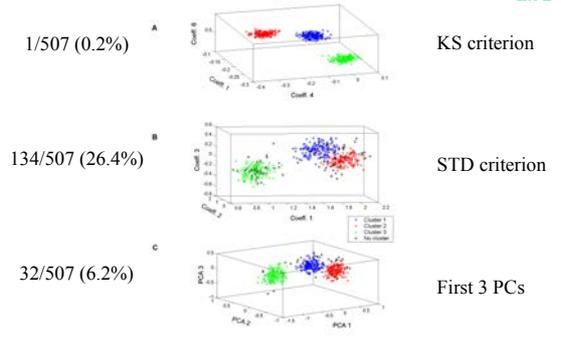
II a - Selection of wavelet coefficients: KS test of Normality



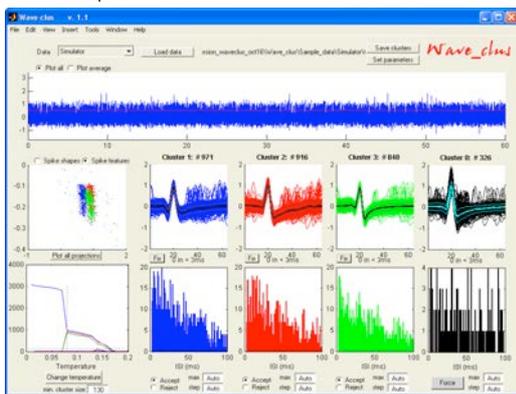
Projections into the feature space

Misses

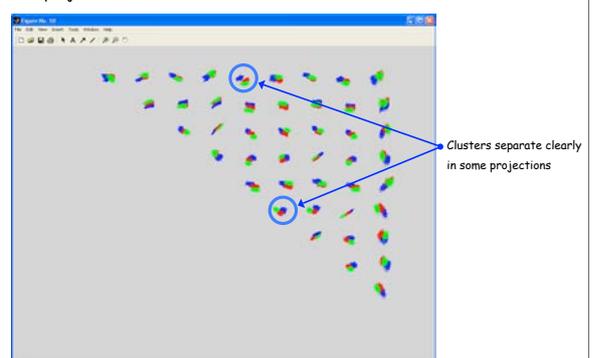
Ex 2



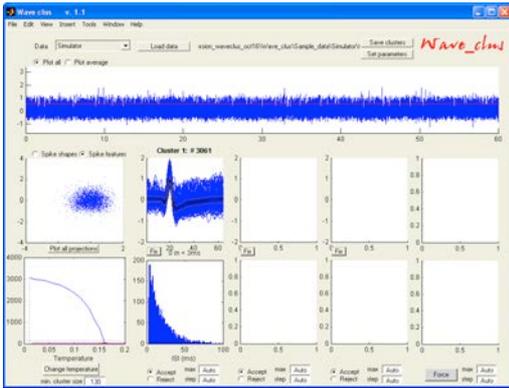
Another example... with wavelets.



All projections...



... and now with PCA



III - Super-paramagnetic clustering

- Automatic clustering algorithm based on ideas from statistical mechanics.
- It's based on nearest-neighbor's interactions.
- Clusters don't need to have a well-defined center, low variance or a Gaussian distribution.

Blatt et al. Phys. Rev. Lett. 76: 3251-3254; 1996.
Blatt et al. Neural Computation 9: 1805-1842; 1997.

Interaction strength

$$J_{ij} = \begin{cases} \frac{1}{K} \exp\left(-\frac{d_{ij}}{2a^2}\right) & \text{if } x_i, x_j \text{ n.n.} \\ 0 & \text{else} \end{cases}$$

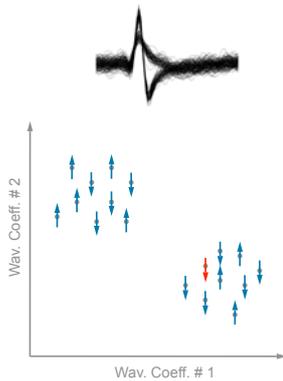
$$d_{ij} = \|x_i - x_j\|^2$$

Probability of change

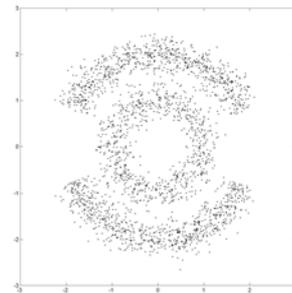
$$p_{ij} = 1 - \exp\left(-\frac{J_{ij}}{T} \delta_{s_i, s_j}\right)$$

Point-to-point correlation

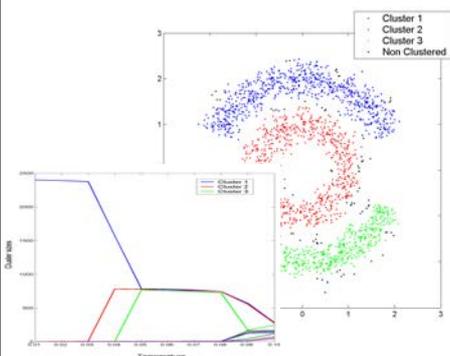
$$\langle \delta_{s_i, s_j} \rangle \geq \theta$$



Toy example



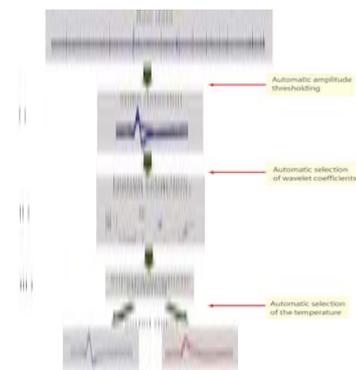
Toy example



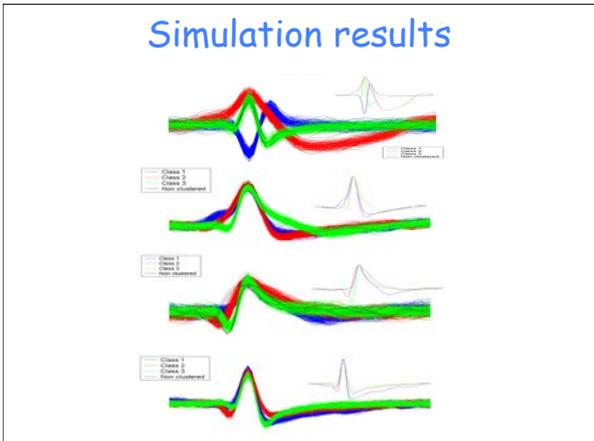
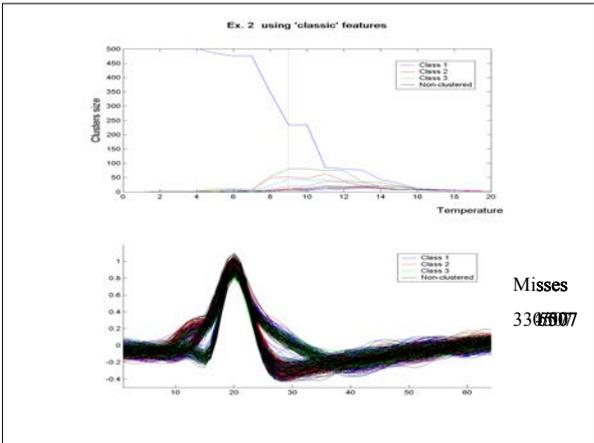
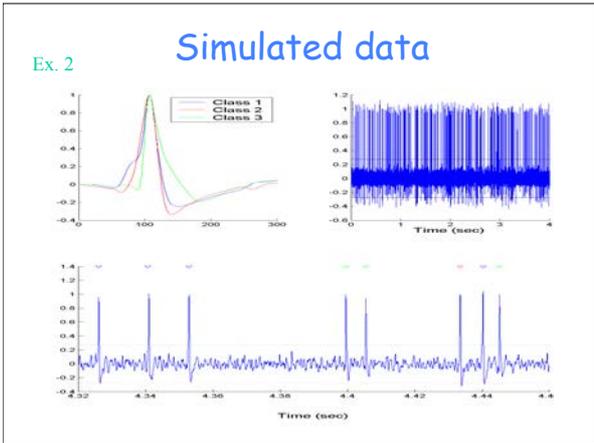
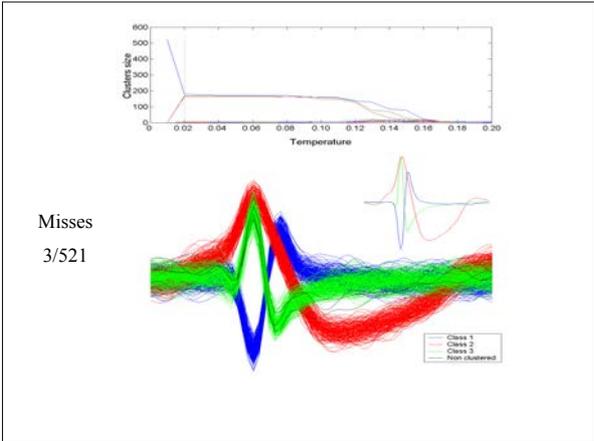
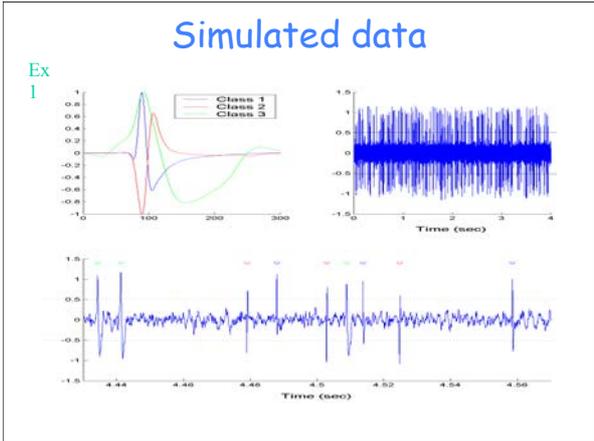
Misses

102/2400

Outline of the method

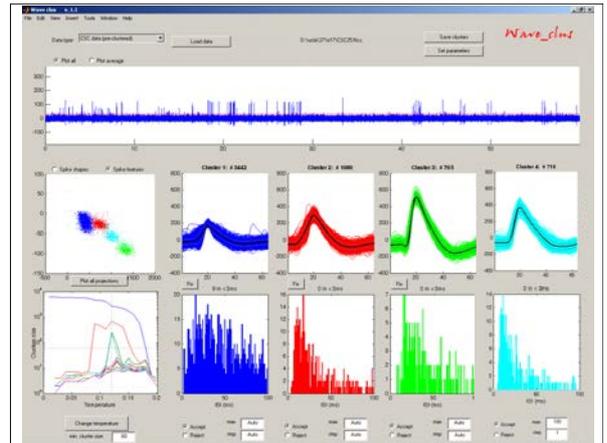


Quijano Quiroga et al. Neural Computation, 2004

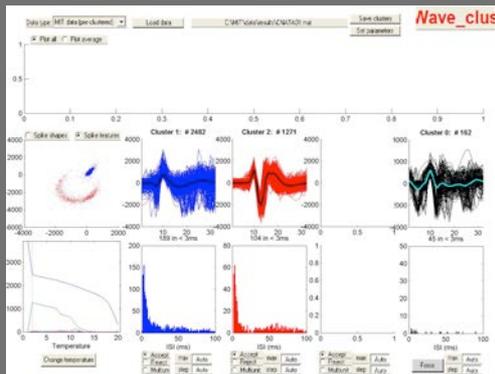


Example #	[noise level]	Nr. of Spikes	Wavelets	PCA		SPC		Feature set	Wavelets	K-means	
				Wavelets	PCA	Splice shape	Wavelets			Wavelets	PCA
Ex. 1	[0.05]	2729	1	1	0	863	0	0	0	0	0
	[0.10]	2753	5	17	0	833	0	0	0	0	0
	[0.15]	2693	5	19	0	2015 (2)	0	0	0	0	0
	[0.20]	2678	12	130	24	614	17	17	17	17	17
	[0.25]	2586	64	911	266	1265 (2)	69	68	69	68	68
	[0.30]	2629	276	1913	838	1699 (1)	177	220	177	220	220
	[0.35]	2702	483	1926 (2)	1424 (2)	1958 (1)	308	515	308	515	515
	[0.40]	2645	741	1738 (1)	1738 (1)	1977 (1)	930	733	930	733	733
Ex. 2	[0.05]	2619	3	4	2	502	0	0	0	0	0
	[0.10]	2694	10	704	59	1893 (1)	2	53	2	53	53
	[0.15]	2648	45	1732 (1)	1054 (2)	2199 (1)	31	336	31	336	336
	[0.20]	2715	306	1791 (1)	2253 (1)	2199 (1)	154	740	154	740	740
Ex. 3	[0.05]	2616	0	7	3	619	0	1	0	1	1
	[0.10]	2638	41	1781	794	1930 (1)	850	184	850	184	184
	[0.15]	2660	81	1748 (1)	2131 (1)	2150 (1)	859	848	859	848	848
	[0.20]	2624	651	1711 (1)	2449 (1)	2185 (1)	874	1170	874	1170	1170
Ex. 4	[0.05]	2535	1	1310	24	1809 (1)	686	212	686	212	212
	[0.10]	2742	8	946 (2)	970 (2)	1987 (1)	271	579	271	579	579
	[0.15]	2631	443	1716 (2)	1709 (1)	2259 (1)	546	746	546	746	746
	[0.20]	2716	1462 (2)	1732 (1)	1732 (1)	1867 (1)	872	1004	872	1004	1004
Average		2662	232	1092	873	1641	332	371	332	371	371

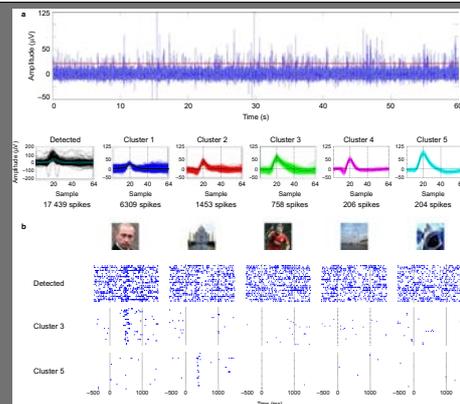
Real data



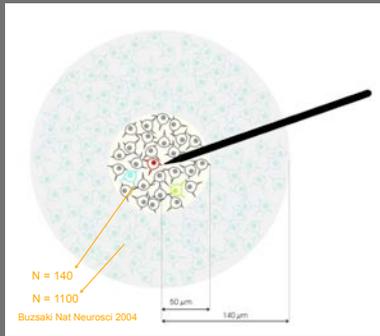
Do we need spike sorting?



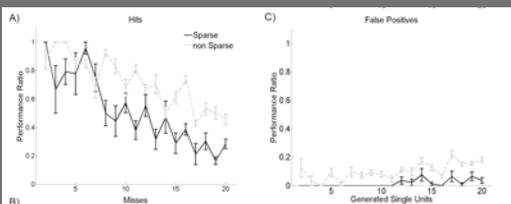
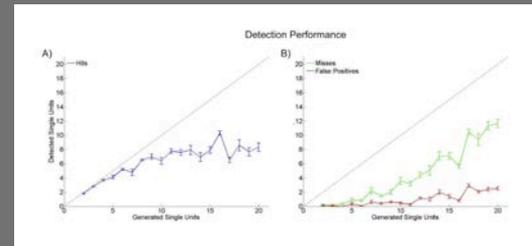
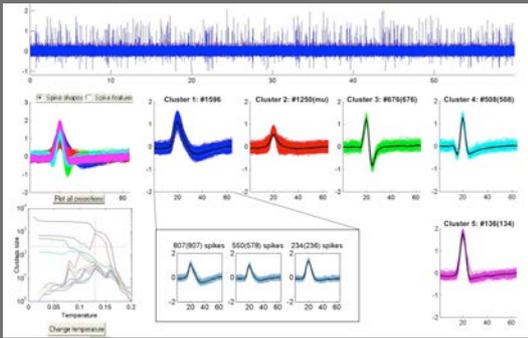
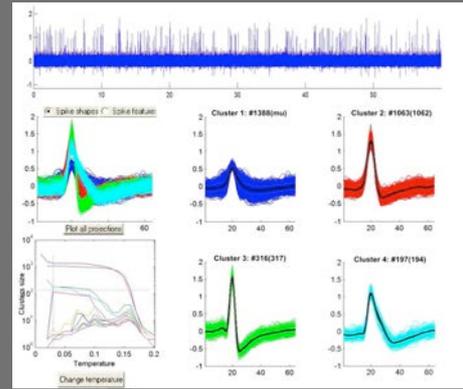
Epilepsy surgery



How many neurons can we see?



Carlos Pedreira
J. Neuroscience Methods, 2012.



Clase 2. Registros extracelulares y Spike sorting.

[A detailed and fast model of extracellular recordings](#)

Luis Camunas-Mesa and Rodrigo Quian Quiroga.
Neural Computation, 25: 1191–1212, 2013

[Unsupervised spike sorting with wavelets and superparamagnetic clustering.](#)

Quian Quiroga R, Nadasdy Z and Ben-Shaul Y.
Neural Computation, 16: 1661-1687, 2004.

[Spike Sorting.](#)

Quian Quiroga R.
Scholarpedia 2 (12): 3583. 2007.

[Quick guide: spike sorting](#)

Quian Quiroga, R.
Current Biology 22. R45–R46, 2012.

[Past, present and future of spike sorting techniques](#)

Hernan Gonzalo Rey, Carlos Pedreira and Rodrigo Quian Quiroga.
Brain Research Bulletin, 119: 106-117, 2015.

