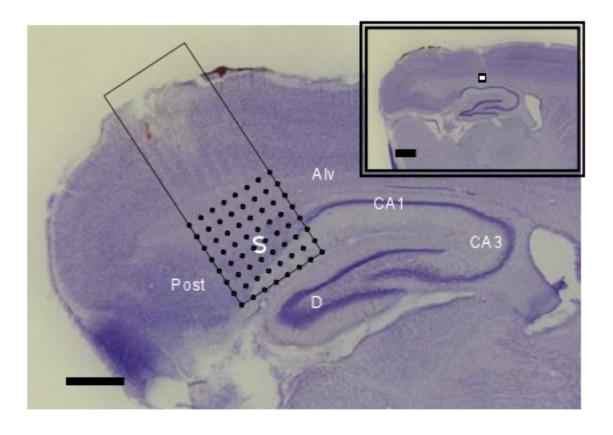
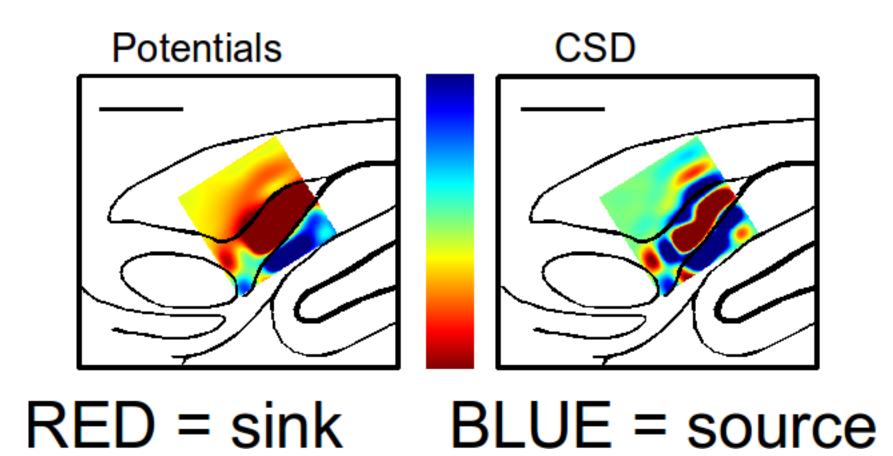
1. Local field potential: local measure of neural activity

Local field potentials (LFPs), the low frequency part of extracellular electric potentials, carry information on brain dynamics at the level of neuronal populations.

To capture the complete response of a brain region to sensory or electric stimulation it is necessary to record the LFPs at many sites simultaneously.





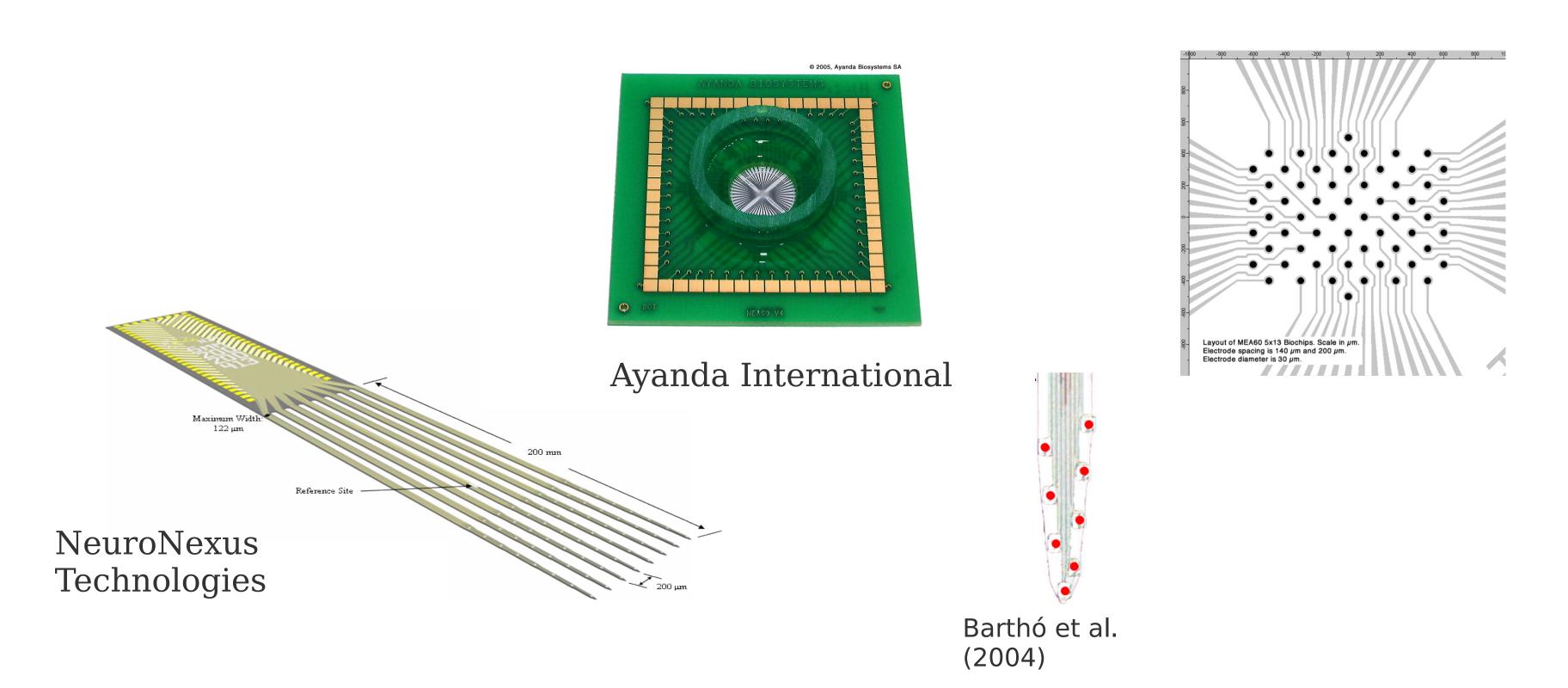
Data: J. Gigg, B. Tunstall

Long range of the electric field in the tissue implies that every source of electric activity (concerted trans-membrane currents) may be visible in recordings at many sites. This complicates the analysis of electrophysiological data.

To study the pattern of activation in complex brain structures it is often of advantage to reconstruct the current source density (CSD), the volume density of net transmembrane currents generating the LFP. Methods for inference of CSD from LFPs are called in neuroscience *Current Source Density methods*.

2. Can we reconstruct CSD from arbitrary distribution of contacts?

In the last few years we have witnessed rapid development of technology for large scale electrical recordings. Various types of multi-electrodes were devised.



Previous CSD inference methods usually required arrangement of electrodes on a regular, rectangular grid. We need a method that will work independent from this assumption.

Kernel Current Source Density Method

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3. Apply kernel methods

We assume CSD from *n*-dimensional linear space (think *n* very large) defined through the basis:

$$\widetilde{F} = \{ \widetilde{f} = a_1 \widetilde{b_1}(x) + \ldots + a_n \widetilde{b_n}(x) \}$$

In 3-D case these functions are the CSD distribution we consider. In 1-D or 2-D we need to specify how CSD is distributed in transverse dimensions: for example, we can assume a cylindrical distribution in 1-D, or a slice of given thickness in 2-D.

Then we use the laws of electrostatics to calculate the potentials b_i corresponding to the basis CSD distributions. The relation is given by a differential operator, in 3-D:

$$\nabla(\sigma\nabla b_i) = -\widetilde{b_i}$$

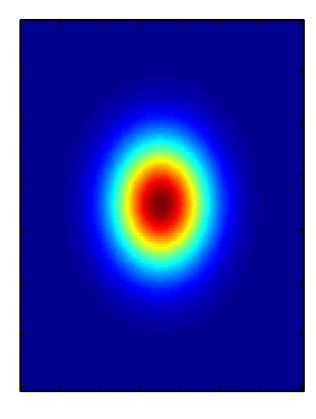
Therefore we obtain the space of possible potential distributions *f*:

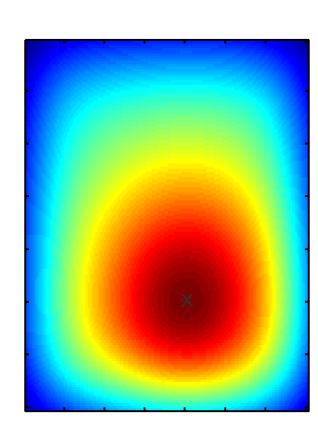
$$F = \{ f = a_1 b_1(x) + \ldots + a_n b_n(x) \}$$

4. From simple bases to smooth kernels

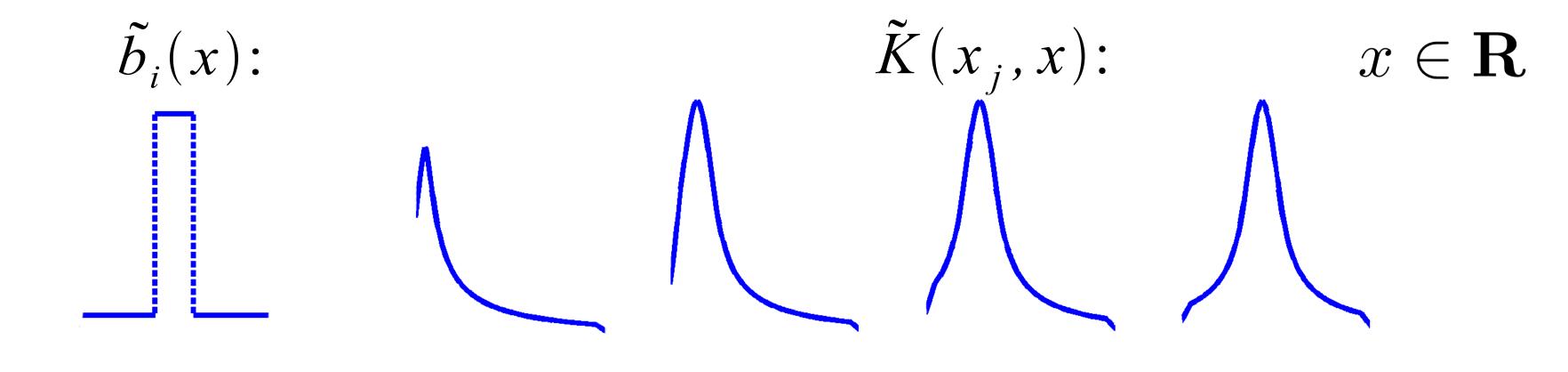
If we start from smooth basis functions we arrive to smooth kernels. For example, as a CSD basis element we can take a Gauss function centered at some point.

 $\tilde{b}_i(x)$:





But the kCSD method can provide smooth CSDs even if space is defined by simple step functions, if only the dimension n is sufficiently high (figure below: $n \sim 1000$).



Despite different shapes of the basis functions we get similar and smooth kernels which points towards the universality of the method.

We define a kernel *K* related to the space *F*:

$$K(x,y) = \sum_{i=1}^{n} b_i(x)b_i(y)$$

and cross-kernel function related to F

$$\widetilde{K}(x,y) = \sum_{i=1}^{n} b_i(x)\widetilde{b}_i(y)$$

(a > bGiven k observation points $(x_j, f_j)_{j=1}^{\kappa}$ the kCSD method returns the 'smoothest' CSD function in *F* that generates the observed potentials f_j at points x_i . This CSD is given as:

$$\widetilde{f}_{\text{est}}(x) = \sum_{j=1}^{k} \beta_j \widetilde{K}(x_j, x)$$

where

$$\vec{\beta} = K^{-1}\vec{f}$$

and the matrix K is $K_{ij} = K(x_i, x_j)$.

0.5 0.5

Model CSD superposed with the positions of recording contacts of a multi-electrode array used in Wirth and Lüscher (2004).

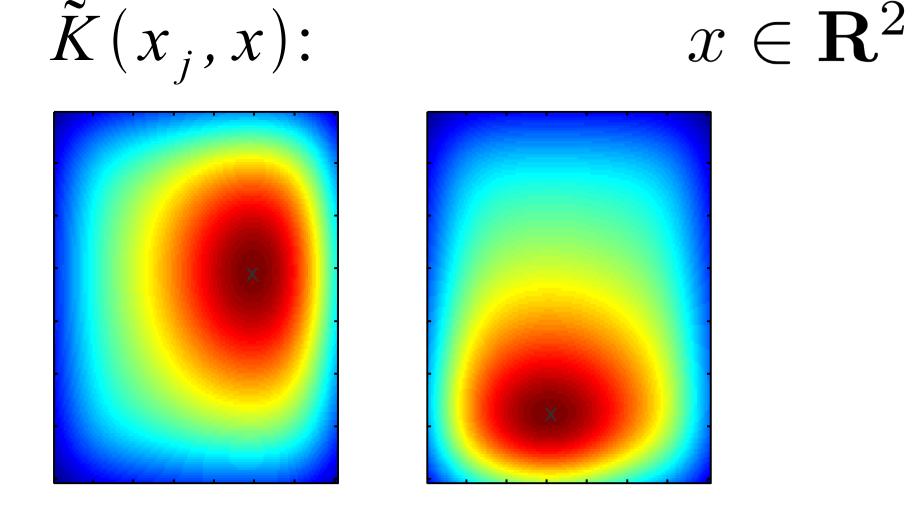
It may happen that a contact or two on a regular multi – electrode breaks. KCSD still works.

Even more, kCSD gives good results for electrodes placed randomly.

References

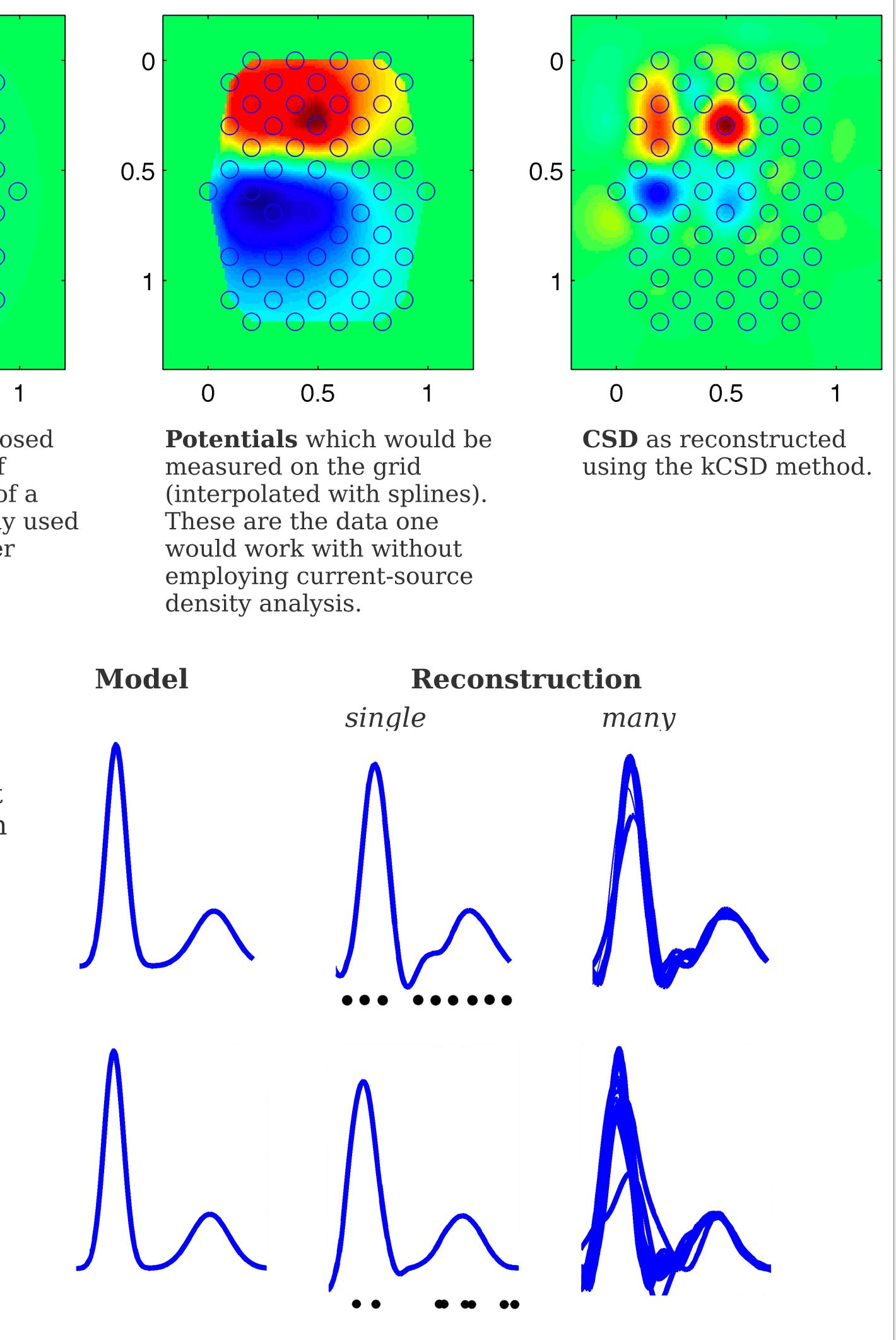
Acknowledgements

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5. Good results for arbitrary electrodes placement

KCSD reconstruction in 2-D



S. Łęski, D.K. Wójcik, J. Tereszczuk, D.A. Świejkowski, E. Kublik, A. Wróbel, Neuroinformatics 5 (2007) 207–222 K.H. Pettersen, A. Devor, I. Ulbert, A.M. Dale, G.T. Einevoll, Journal of Neuroscience Methods 154 (2006) 116–133 D. K. Wójcik, S. Łęski, Neural Computation 22 (2010) 48-60 P. Barthó, H. Hirase, L. Monconduit, M. Zugaro, K.D. Harris, G.Buzsáki, Journal of Neurophysiology 92 (2004) 600–608 C. Wirth, H.-R. Lüscher, Journal of Neurophysiology 91 (2004) 1635–1647