Reverse-engineering of the visual brain cortical maps computation using optical-imaging

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We asked whether optical imaging could be used to characterize the underlying computations given the activity of a brain area.

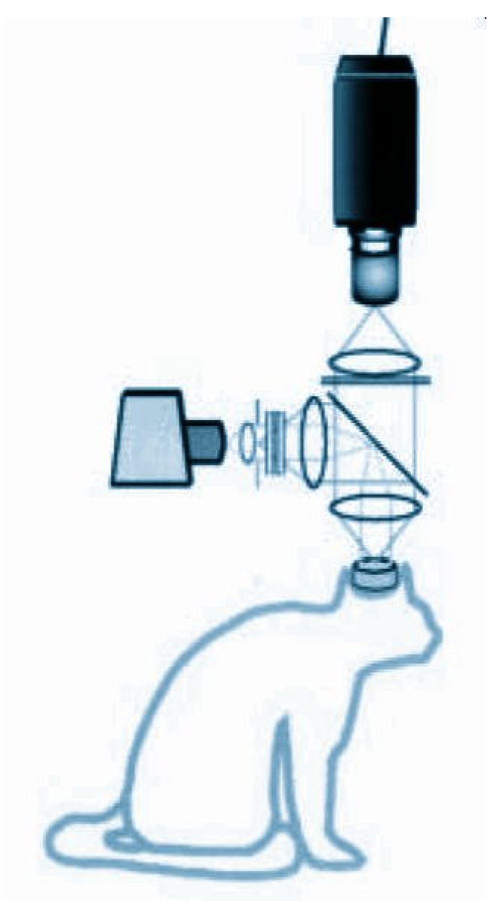
If biological neural network information is mainly related to the synaptic input (thus to the membrane potential in this case), it is however usually modeled with high-level representation of the related processing (e.g. variational specification of neural-map computation in relation to local diffusion mechanisms in neural networks), allowing to relate the observed activity with certain classes of underlying computations (e.g.: early-vision processes, winner-take-all mechanisms, etc.).

Neuronal activity diffusion estimation seems feasible, given the proposed assumptions and actual data sets. Further investigation on diffusion map recovery are in progress.

Goals

- We propose to evaluate, given the activity of a spiking network which related membrane potential is measured using optical-imaging (here during the observation of V1), what is the underlying diffusion process? This is a highly constrained meso-scopic model of the neuronal activity, likely more robust to estimate than in a less specific case.
- Considering a very simple experimental paradigm, we analyze if the precision of the data is sufficient to estimate robustly the underlying diffusion mechanisms.
- More generally, we propose to estimate the required precision in terms of scale and dynamics for such a reverse-engineering paradigm to be valid.

Optical imaging & cortical activity observation

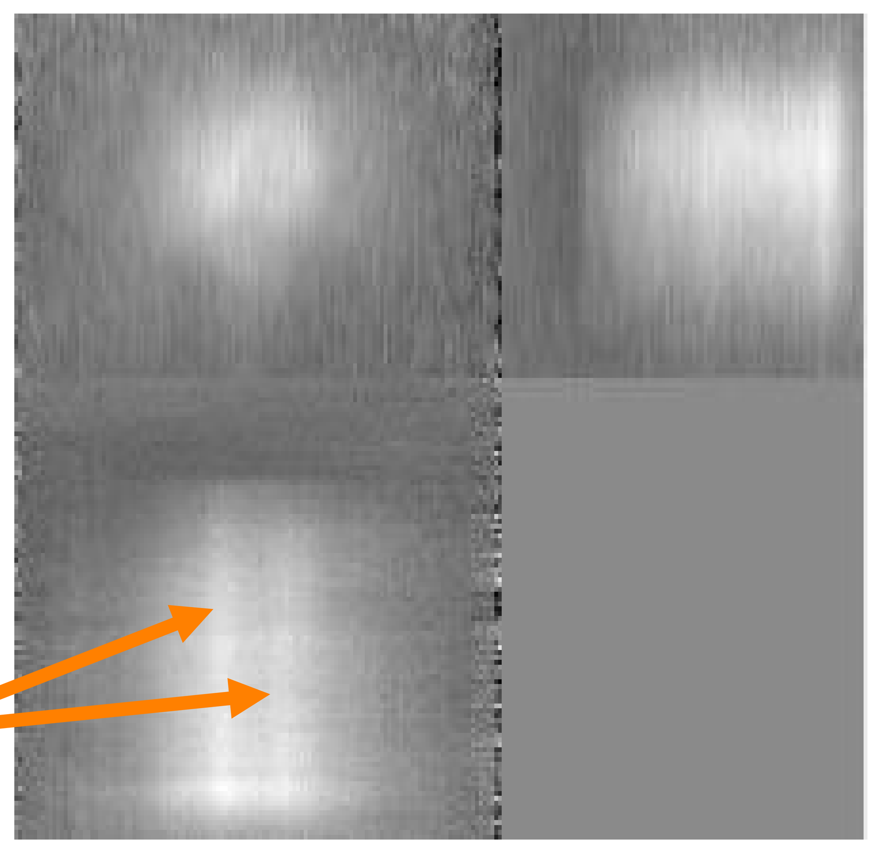


- Optical imaging of cortical activity based on real-time imaging using extrinsic dye-signals gives a meso-scopic view of changes in membrane potential.
- Particularly sub- and supra-threshold synaptic potentials of cortical layers III and IV (resolution of about 100µm e.g. < 10^3 neurons)
- Observation of the functional organization of the cortical columns.

Example of V1 dye-signal in the cat, after a visual local stimulation:

- Top-left view shows the diffusion at the middle of the record.
- Right and bottom spatio-temporal views show the evolution of the signal

Here, two columns are clearly stimulated.



Position of the problem

- Given a variable 2D activity map *s(p, t)* related to a diffusion mechanism at each point ***p*** and time *t* :

$$\dot{s} = \Delta_{\mathbf{L}}\, s + e$$

the goal is to estimate
  - The diffusion operator ***L***.
  - And eventually the sparse input *e(**p**, t)*.

- We consider a discrete integral approximation of the diffusion operator defined in a neighbourhood of ***p***.

- We define the estimation via a criterion of the form:

$$\min_{\mathbf{L},e} \int \underbrace{[-\dot{s} + \Delta_{\mathbf{L}}\, s + e]^2}_{1} + \underbrace{\Phi(||\nabla_{\mathbf{p}}\mathbf{L}||)}_{2} + \underbrace{\psi(e)}_{3} + \underbrace{\lambda\, \kappa(\mathbf{L})}_{4}$$

6. Minimizing the estimation error of ***L***

2. With non-linear isotropic regularisation of ***L***

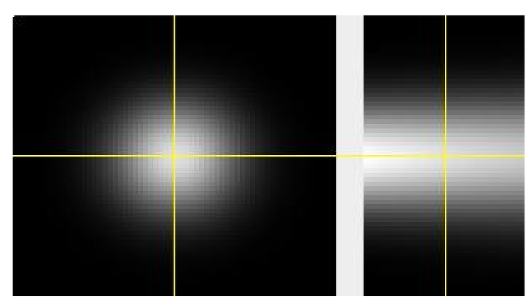
3. While the input *e()* is constrained to be sparse

4. Introducing unbiasness constraints for ***L***:
   4.1 Either uniform isotropic (and Gaussian) diffusion
   4.2 Or constant (in time) isotropic diffusion
   4.3 Or time and space variable isotropic diffusion
   while other alternatives can easily be introduced.

- The estimation is implemented calculating the Euler-Lagrange equation of the previous criterion, easy to implement.

Preliminary results

- Using synthetic data with a sparse source and isotropic noisy diffusion (virtual Phantom)
  - The estimation data has been validated.
  - Its robustness quantified for assumption 4.2



Input noise magnitude	0	10^{-6}	10^{-5}	10^{-4}	10^{-3}
Signal standard-deviation	$5\,10^{-2}$	1.4	14	$1.5\,10^{2}$	$1.6\,10^{3}$
Estimation standard-deviation	$5.5\,10^{-6}$	$0.5\,10^{-5}$	$1.05\,10^{-4}$	$0.95\,10^{-3}$	0.99

(given an input noise, highly magnified in the signal by the diffusion, the estimation uncertainty remains correct, the last column corresponds to the expected real-data noise-level)

- Using real data we have been able to recover some diffusion estimation and have observed that estimating diffusion under assumption 4.1 and 4.2 seems significant (while assumption 4.3 is not statistically significant with the present data set)

References

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