How does neuronal variability impact decoding of visual features?

An interdisciplinary project across machine learning and retinal electrophysiology, involving the Paris Vision Institute and the ENS Physics Laboratory.

U. Ferrari (CNRS-CR, HDR, ED3C, Paris Vision Institute) is an expert of machine learning applied to retinal electrophysiology, with a strongly data-driven approach.

T. Mora (CNRS-DR, HDR, EDPIF, Q-Bio, ENS) has a long-standing expertise in systems biology, computational neuroscience and statistical physics.

Collaboration. T. Mora and U. Ferrari collaborated since 2014 and have already co-supervised the thesis of G. Mahuas [1,2,3]. They both collaborate closely with O. Marre (Paris Vision Institute), who will provide access to retinal recordings.

Context and purpose. Deep convolutional neural networks (DNNs) share similarities with biological visual systems, including layered structures and filtering stages [4]. However, DNNs use deterministic, dense signals, while neurons communicate with sparse, noisy spikes. This biological approach is far more energy-efficient: the human brain uses only 20W [5], compared to the huge consumption of modern AI. The trade-off for this efficiency is reduced reliability due to neuronal noise. Surprisingly, this doesn't significantly impair animals' high performance in behavioral tasks, like the visual ones. All the visual information accessible to the brain is encoded by the retina into its stochastic spiking response to stimulus. **How can the brain extract visual features from such noisy inputs?**

In addition to noise of individual neurons, it has been shown that stochastic retinal spiking is correlated among nearby cells in the same layer [6], an effect termed "noise-correlation" – as opposed to stimulus-induced correlations. The role of noise correlations is still unclear and remains an active research topic in neuroscience [3,7]. **Our working hypothesis is that correlations can mitigate detrimental effects of noise on information transmission**. We will test this hypothesis through neuronal decoding and image classification using the retinal spiking response as input.

Research plan. After a review of the relevant literature (M1-3), the PhD candidate will focus on computational models of the retinal response to stimulus (M4-12) For this, we will build on our framework for inferring **deep generative models that reproduce retinal correlated variability** [1]. The use of models capable of generating synthetic, but *realistic* data will be key for the following steps. O. Marre will provide previous data and perform new experiments where a behaviorally relevant feature, like a moving object, is superimposed to natural videos (rich background). Additionally we will also measure and then model the retinal response to images suited for classification, as for example, those of imagenet, similarly to what we have done in the past [7].

Once faithful retinal models are constructed, the PhD candidate will develop non-linear decoders that take as input the retinal spikes generated by our models. These decoders will perform either feature extraction or image classification (M13-20). Previous work on retinal decoding mostly focused on the stimulus reconstruction pixel-by-pixel

[9,10], or to stimulus composed only by a single feature and empty background [11], something far from the actual tasks that the brain might address. Here we will focus on high dimensional stimuli, and solve behaviorally-relevant decoding problems.

M21-28 will focus on the impact of noise correlation on the decoding performance. Using our retinal generative models, it will be possible to tune those correlations while simulating the retinal response, and therefore test the decoding or classification performance in different conditions. Either possible outcomes will be interesting for the community. Based on our previous results [3], we have strong expectations for the correlations to be beneficial for the feature extraction task. Consistently, recent preliminary results support those expectations: noise correlations increase the performance of a bayesian decoder of a one-dimensional stimulus. **This project aims at extending these preliminary results to high-dimensional and highly non-linear settings.**

The project will end (M29-36) by paper and manuscript writing and PhD defence.

Perspectives. Most of the work addressing stimulus encoding in the retina tackles the problem from the retinal standpoint itself. Here, thanks to non-linear decoding and image classification, we extend this perspective from the point of view of the brain.

Interdisciplinary flavour. This project combines our expertise in machine learning and computational neuroscience with data from electrophysiological experiments, carried out by O. Marre's team at the Paris Vision Institute.

Feasibility. Our long standing collaboration has been proven successful with several published papers and the co-supervision of one PhD student and several internships. Although tested in simple settings, preliminary results obtained recently are encouraging. A significant part of the retinal data and models are already available from previous research.

PostGenIA@SU. This project will develop the application of computer science to neuronal activity, including the development of generative models for spiking activity, and paving the way towards more reliable brain machine interfaces for health.

Candidate. We look for a student with a master in any computational field and a strong interest towards data-driven application of computer science, in neuroscience or elsewhere.

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