Decoding orientation and variability of visual stimulus in V1

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Abstract

The aim of this project is to study different **machine learning** methods and compare them in order to improve the performance of **decoding neural activity** recorded in the cat's primary visual cortex. In particular, different mathematical **preprocessing** transformations would make it possible to modify the decoder's accuracy based on the assumption that decoding the **neural code** does not rely directly, or at least not entirely, on the firing rate. In this work, we have qualitatively demonstrated that histogram equalization improves the decoding performed by a **multinomial logistic regression model**, less so in the case for the error function. This work highlights the importance of finding the right preprocessing method to bring out the most useful information for the decoder.

Introduction

In order to apprehend the visual information that constitutes the environment, the nervous system translates and processes all the related information into a complex neuronal activity in order to create an internal representation that can be used for decision-making, for example estimating the main orientation of a scene. Indeed, it has been shown that the firing rate of neurons in the primary visual cortex (V1) reacts differently depending on the orientation of the stimulus[3], but also on its contrast[1].

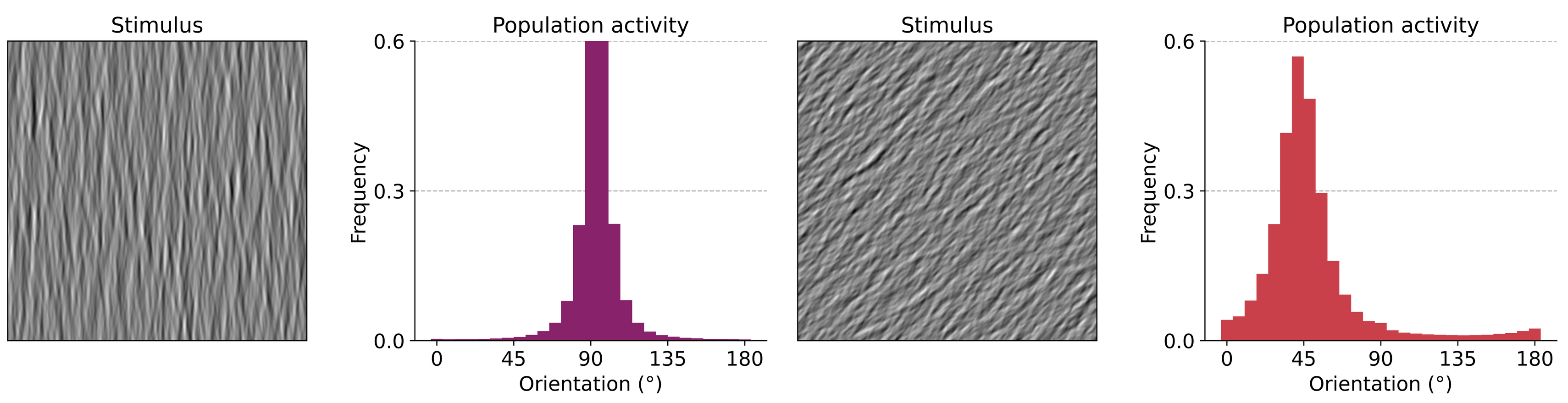

Figure 1 : Activity of the neuronal population for different stimuli[4].

This information encoded by the neuronal activity, for example in the form of a firing rate, a time-dependent activity or a recurrent pattern, constitutes the neural code. By using mathematical models, decoding attempts to learn this code in order to find the stimulus that induced a certain neuronal activity. However, as the information to be translated by the model is complex and noisy, one way of improving decoding is to add a preprocessing phase that modifies the medium with which the decoder works. To do this, we use two non-linear transformations and estimate their influence on the accuracy of the model's predictions.

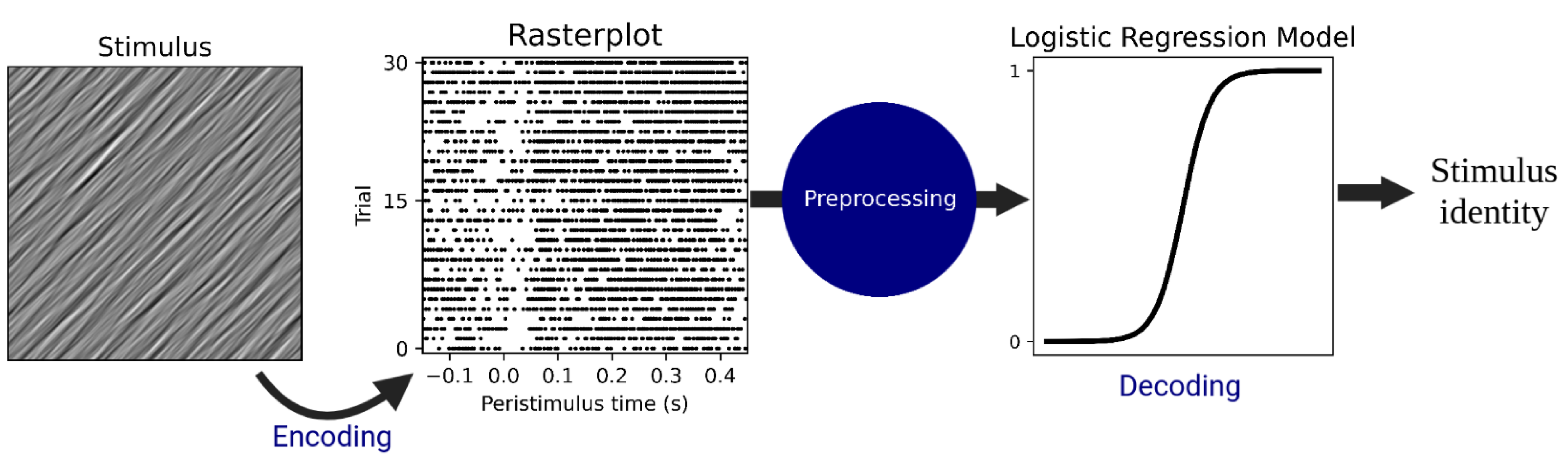

Figure 2 : Decoding the populationnal activity.

Methods

⇒ *Visual stimulation and electrophysiological recording*

The data was collected during *in-vivo* electrophysiological recordings in 3 cats during which the visual stimuli are produced by the Motion Cloud[5] model, allowing control of stimulus orientation (θ) and variability (B_θ). Recording is performed over 12 orientations (from 0 to 180°) and 8 variability (from 0° to 36°), giving a total of 96 possible combinations.

⇒ *Preprocessing*

1. Histogram equalisation[6] : Non-linear transformation from a real positive variable (here, with a Poisson-like distribution) to a scalar which is uniformly distributed between 0 and 1. In our case, this non-linear transformation (or rescaling) results in a uniformity that lowers the impact of maximal points of information, while raising the impact of minimum points of information, therefore reducing the impact of outliers.

$$z_i(\bar{a}_i) = P_i(a_i \leq \bar{a}_i) = \int_{-\infty}^{\bar{a}_i} dP_i(a_i)$$

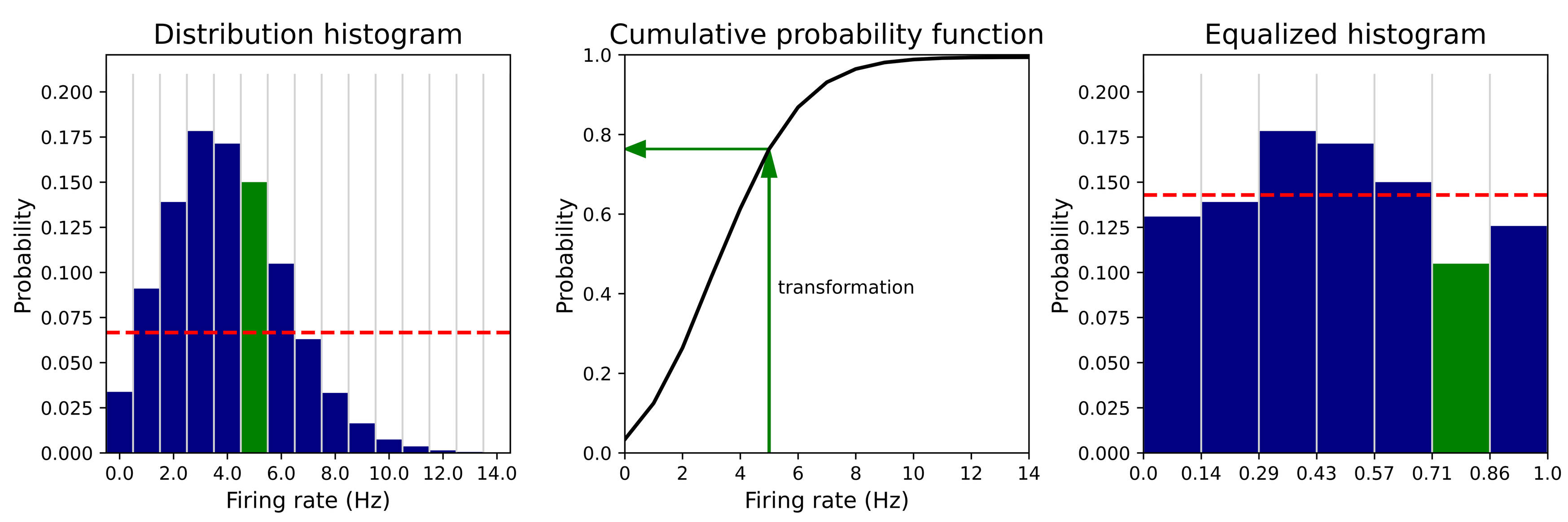

Figure 3 : Histogram equalization preprocessing.

2. Inverse error function : We also tested a non-linear transformation which rescales firing rates towards a normal distribution, thus resembling more closely a "natural" distribution.

$$z_i' = \text{erf}^{-1}(z) \text{ with } \text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt$$

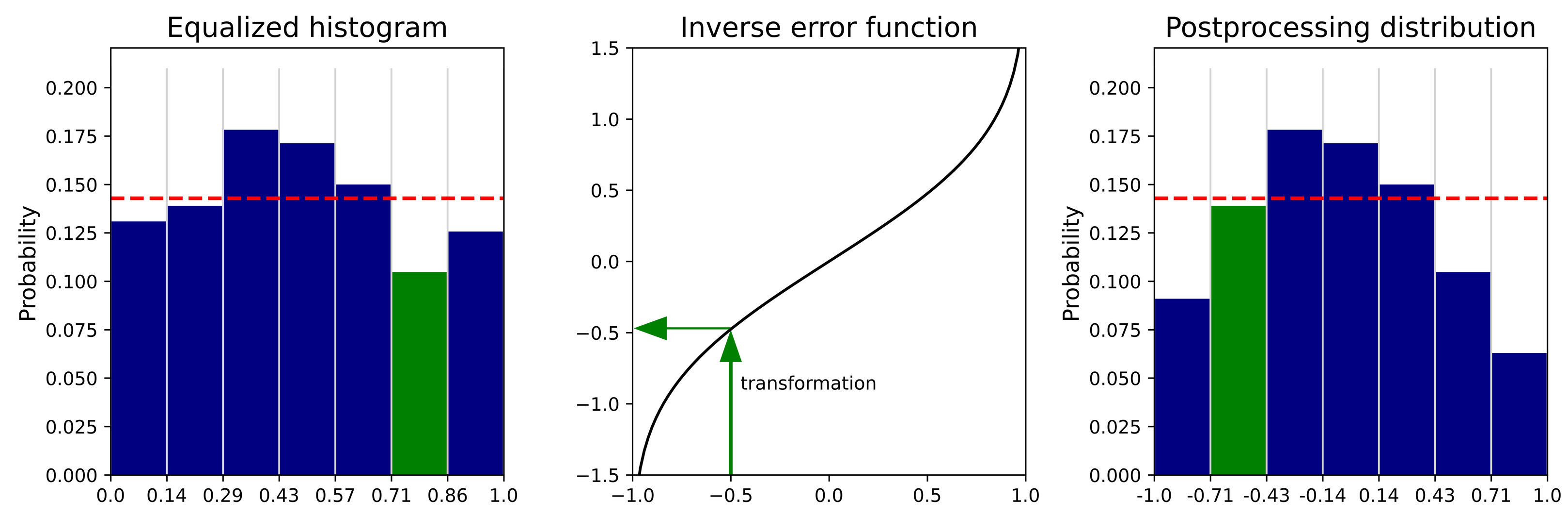

Figure 4 : Second stage of preprocessing.

⇒ *Decoding with multinomial logistic regression*

In order to decode the recorded data, the model used in supervised learning is a multinomial logistic regression[2], with optimized learning parameters to obtain the best classification accuracy. The aim of this model is to estimate the most likely stimulus identity ($k \in K$), which could be θ ($K = 12$), B_θ ($K = 8$) or $\theta \times B_\theta$ ($K = 96$), in function of the temporal activity of the neuronal population.

$$P(y = k|X(t)) = \frac{\exp\langle \beta_k, X(t) \rangle}{\sum_{1 \leq k' \leq K} \exp\langle \beta_{k'}, X(t) \rangle}$$

Results

The decoding of the orientation θ shows a progressive increase of the improvements allowed by the histogram equalisation when the variability B_θ decreases (**Fig.5**). Regardless of the method used, the decoding of variability does not seem to be noticeably influenced by the transformations performed (**Fig.6-A**). Stimulus identity decoding is by far the most complex element, but is improved by the methods used (**Fig.6-B**). The improvements seem to take place mainly between -0.5 and 0.5 s around the presentation of the stimulus. On the other hand, there was no difference between equalisation alone and the combination of the two transformations.

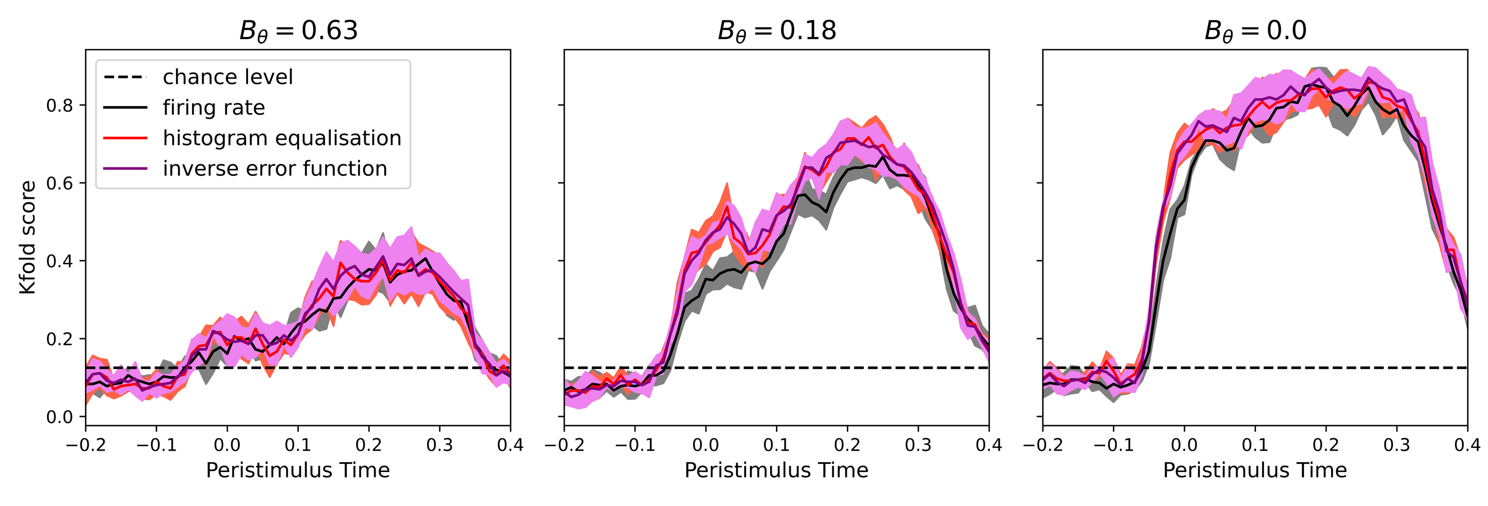

Figure 5 : Decoding the θ orientation for different B_θ variability.

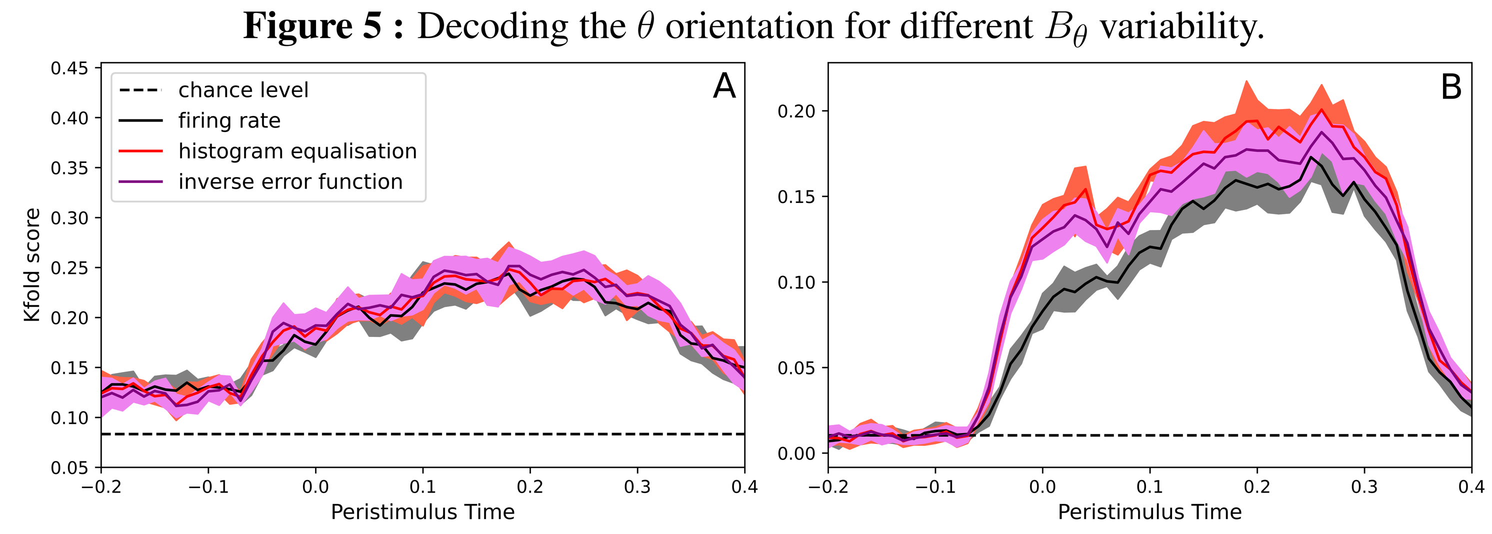

Figure 6 : Decoding (**A**) the B_θ variability, and (**B**) the stimulus identity (θ and B_θ).

Conclusion

The addition of a preprocessing step is an interesting addition from the point of view of improving the decoding of neuronal activity. Using these rescaling transformations redistributes the data to make it easier for the decoder to interpret, and it seems to be particularly efficeint when activity is more variable between individuals or between neurons. Separating neurons according to the specificity of their responses, such as the presence of a population of neurons resilient to stimulus variability[4], would be an important distinction that would reduce the quantity of data, but also the ambient noise generated by these non-coding neurons.

References

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