Electrolocation of prey-like stimuli: a detection-theoretic approach

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Sensory systems have evolved under the constraints of their natural environment. Consequently, it is expected that neural circuitry at the early levels of sensory processing should implement matched spatiotemporal filters that are adapted to the behaviorally relevant components of natural stimuli.

Electrosensory image processing

We consider the electrosensory system of a weakly electric fish (*Apteronotus albifrons*) as a model system for studying sensory filtering. One of the behaviorally relevant tasks for this animal is the detection of small prey (e.g. the "water flea" *Daphnia magna)*. The prey causes small perturbations of the fish's self-generated electric field, resulting in a transcutaneous voltage change across large parts of the body surface ("electrosensory image") that can be perceived by the fish through electroreceptors embedded in the skin. Since there is no focusing mechanism in electrosensation, the electrosensory image of a small object in close proximity is a blurred pattern, broadly distributed over a significant number of electroreceptors.

The first stage of detection is believed to be performed by basilar pyramidal cells in a nucleus in the hindbrain, called the electrosensory lateral line lobe (ELL). Each basilar pyramidal cell receives direct input from peripheral electroreceptors transmitted through afferent nerve fibers.

Since the electrosensory image is an extremely weak signal, the sensory input encoded in the stochastic afferent activities is virtually obscured by the intrinsic noise, i.e., the signal to noise ratio is much less than unity (i.e., SNR << 0 db). The fish thus has to solve a challenging detection task that can be posed as a classical problem of hypothesis testing in statistical signal detection theory.

We consider a situation, wherein the target suddenly appears at an arbitrary location. One may imagine a scenario in which the prey is dropping from the leaves of trees overhanging the riverbanks, with the fish swimming close to the water surface.Although dynamical parameters, such as target motion or the temporal structure of receptive fields, certainly influence the detection process, our analysis focuses on the spatial aspects of the problem. We demonstrate that our simplified model captures - at least qualitatively - typical *spatial* characteristics of the detection performance. In accordance with behavioral and physiological data, the model predicts receptive field size as well as the existence of a highly limited detection range with a sharp boundary.

Statistical detection-theoretic analysis

Statistical detection theory provides a criterion for an optimal detector. Let $\vec{a}$ be the "data vector" (the set of afferent activities). According to the Neyman-Pearson theorem the ratio of data likelihoods under assumptions of signal presence (hypothesis H_1) or absence (hypothesis H_0), respectively, is to be compared to a threshold γ:

$$\ln \frac{p(\vec{a};H_1)}{p(\vec{a};H_0)} \quad > \quad \gamma$$

The Neyman-Pearson theorem then guarantees that a detector that decides H_1, if the threshold is exceeded, has maximum probability of detection [3]**.** The value of γ has to be set according to the desired probability of false alarm. Gold and Shadlen [1, 2] suggested neural correlates of the above formalism and showed that the logarithm of a likelihood ratio can be represented by a linear function of the sensory input. Since it is sufficient to compute a monotonic function of the likelihood ratio, even a simple model neuron might thus have the computational power to constitute an NP-like detector.

In the analogy to biological detector neurons, the likelihood ratio corresponds to the membrane potential of a sensory neuron (such as a basilar pyramidal neuron in the ELL), and the "decision H_1" is equivalent to generating an action potential. Since the ELL is not the site of an actual behavioral decision, but merely a first stage of processing, it can be regarded as a set of matched filters detecting expected patterns of input.

The Bayesian formalism offers a means of incorporating pre-existing knowledge about the stimuli into the Neyman-Pearson (NP) criterion, through the prior distribution of unknown stimulus parameters. However, the resulting integrals are often impossible to compute in closed form and therefore require some kind of approximation.

Interestingly, an approximation of the Bayesian form of the NP-detector, by means of Jensen's inequality, leads to a simple sub-optimal detector that is biologically plausible, in a computational sense, and still provides a good detection performance. In particular, we demonstrate that the approximated Bayesian detector consists of a weighted sum of inputs, which is structurally identical to the linear summation term of an integrate-and-fire neuron.

We show that such approximation of the optimal Bayesian detector is best for increasing noise level, i.e. under biologically plausible conditions. A real sensory neuron should be at least as powerful as the linear integrate-and-fire model and can thus be expected to exhibit near-optimal detection performance.

References

[1] Gold, J.I. and Shadlen, M.N. (2001) "Neural Computations that Underlie Decisions About Sensory Stimuli", *Trends in Cognitive Sciences,* vol. 5(1), pp.10-16

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