"Smart sensing" strategies for detection and tracking using multiresolution spatiotemporal filtering

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Introduction

Sensory systems employ a variety of mechanisms to efficiently acquire, extract, and process information that is needed to guide behavior. Collectively, these mechanisms can give rise to an emergent mode of operation that we refer to as *smart sensing*. Smart sensing is not a single mechanism or algorithm. Rather it is the result of systems-level integration of multiple cooperative mechanisms such as dynamic positioning of the sensor array, task-specific adaptive filtering, attentional mechanisms, and the subtraction of sensory expectation. Our research attempts to understand how these mechanisms are implemented in the nervous system and how they are integrated at the systems level. Specifically, we investigate how movement strategies, sensory coding mechanisms, and hindbrain neural processing properties are integrated during prey capture behavior in weakly electric fish.

Mutliple maps in the hindbrain

One of the components of a smart sensing strategy involves employing the proper spatial and temporal filtering properties to enhance signals of behavioral relevance and to suppress unwanted background noise. In the electrosensory system, spatiotemporal filtering takes place in a hindbrain sensory nucleus called the electrosensory lateral line lobe (ELL). Primary afferent nerve fibers, arising from about 15,000 electroreceptors on the skin, project to the ELL. In the fish that we study (*Apteronotus albifrons*, black ghost knifefish), the ELL is divided into four somatotopic maps (Heiligenberg and Dye 1982; Shumway 1989ab). The medial map processes information from the passive electrosense, while the other three maps process information from the active electrosense. Afferents associated with the active electrosense provide the three lateral maps (centromedial, centrolateral and lateral) with essentially identical input. This input is then processed with spatial and temporal filtering properties unique to each map. In general, there is a tradeoff between sensitivity and spatial resolution across the three maps. The lateral map has the highest degree of peripheral convergence and thus the best sensitivity to weak stimuli, but has poor spatial resolution. In contrast, the centromedial map has good spatial resolution but low sensitivity. As illustrated in Fig. 1, the ELL can thus be envisioned as a bank of adjustable multiresolution filters.
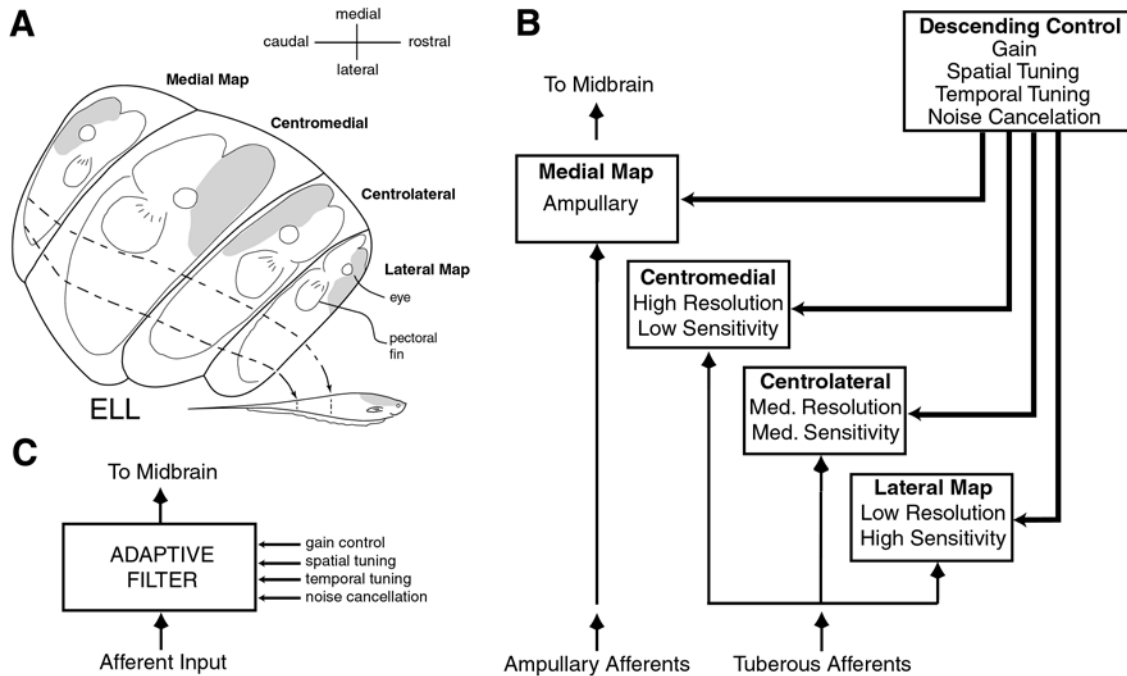
Fig. 1 *Schematic of the ELL as a multiresolution adaptive filter array. (A) Dorsal-ventral projection of the right ELL showing the four somatotopic maps of ampullary and tuberous electrosensory input (shaded area was out of water and not mapped). Modified from Heiligenberg and Dye (1982). (B) Each map receives essentially identical afferent input, but processes that input with unique spatiotemporal filtering characteristics. (C) Each map can be thought of as an adaptive filter module with descending signals providing gain control, spatiotemporal tuning, and suppression of certain types of background noise.*

Prey capture behavior

Previous studies in our laboratory have characterized movement trajectories and the resulting electrosensory image characteristics during prey capture behavior (Nelson and MacIver, 1999; MacIver et al., 2001; Nelson et al. 2002). As illustrated in Figure 2, the electrosensory image of the prey on the skin is a Gaussian-like "bump" that sweeps over the receptor array due to relative motion between the fish and prey. One interesting aspect of the problem is that the spatiotemporal properties of the image change rapidly over the course of the prey capture trajectory. Rasnow (1996) has shown that the full-width at half-max (FWHM) of the image is approximately equal to the distance between the prey and the receptor array. Thus, when the prey is a few centimeters away from the fish it casts an electrosensory image with a FWHM of a few centimeters. Later in the capture sequence, when the prey is only a few millimeters from the skin, the FWHM of the electrosensory image is an order of magnitude smaller than in the beginning. These changing spatial profiles are translated into changing temporal profiles due to relative motion between the fish and prey.
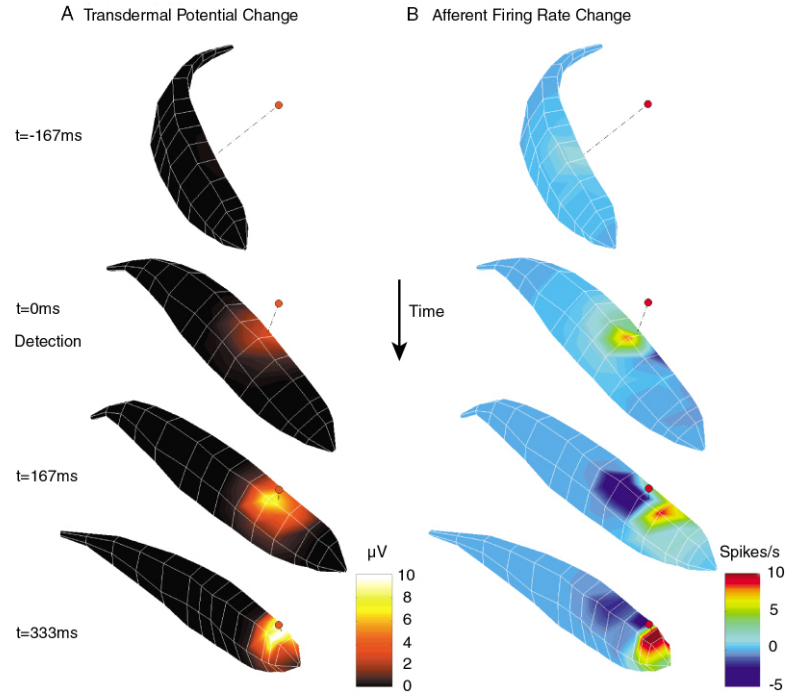
Fig. 2 Reconstructed electrosensory images based on infrared video recordings of prey capture behavior. Selected 'snapshots' showing the 3-D geometry and electrosensory images at four time points during a representative prey-capture sequence. Time (in ms) runs vertically from top to bottom; times are measured relative to prey detection (t=0). The left-hand column (A) shows the change in transdermal potential induced by the prey (red ball). The right-hand column (B) shows the corresponding change in afferent spike activity (in spikes/s). Modified from Nelson and MacIver (1999).

Detection and tracking using multiple spatiotemporal filters

Efficient detection and tracking of the prey requires that the incoming signals be filtered in a manner that matches the spatial and temporal characteristics of the electrosensory image. As illustrated in Fig. 1, the ELL provides an appropriate neural substrate for implementing multiresolution filtering algorithms. In the study presented here, we use signal detection and estimation theory to test the hypothesis that combining information from three multiresolution maps will significantly enhance detection and tracking performance relative to a single map with fixed spatiotemporal characteristics. First we will use the known spatiotemporal filtering properties of each of the three ELL maps to assess detection and tracking performance for each map individually. Then we will test the performance of an algorithm that combines information across all three maps.

Preliminary analysis suggests that the multiple maps in the ELL have different performance characteristics during different stages of the behavior. The lateral map, which has large receptive fields and a high sensitivity due to extensive convergence from the periphery, appears ideal for mediating the initial detection of the signal, since

detection requires integrating signals from a weak electrosensory image that is distributed over a relatively large area of the receptor surface. The centromedial map, which has less convergence and better spatial resolution, may be better matched to the final localization stage of prey capture when the electrosensory image is spatially restricted and much stronger. Quantitative estimates of detection and tracking performance will help us better understand the extent to which multiresolution filtering in the ELL may contribute to the smart sensing capabilities of the system.

Models of signal detection
In order to gain deeper insight into the detection problem the fish are confronted with, we perform computer simulations aiming to compare the fish's exceptional detection performance with detector models derived from principles of signal detection theory.

We consider abstract detector models in which the electrosensory image on the skin caused by a nearby object is approximated by a Gaussian "bump" with added Gaussian noise. Due to the low signal to noise ratio (SNR << 0 db), the image is virtually obscured by the noise. A detector system capable of reliably detecting such a weak signal necessarily involves the pooling of receptor activities across the population as well as an averaging over time in order to suppress the large noise component. To a first approximation, a suitable detector can be modeled by a leaky integrator with an appropriate integration time constant, which sums up receptor activities over a Gaussian receptive field and responds when the sum exceeds a threshold.

Technically speaking, the task is to detect a signal with an expected structure within the noisy input. Since the detector algorithm accumulates information over time, there is a trade-off between rapid detection and avoiding false alarms. The performance of a given detector model can be assessed in terms of how well it accomplishes such a trade-off. The result can then be compared to theoretical optimal detectors, such as the *likelihood ratio test* defined in the Neyman-Pearson theorem, known from statistical signal detection theory (Kay 1998). Commencing with rather abstract detection schemes, we gradually increase the model complexity by taking into account more and more biological details.

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