

Highlights

Ecological decision-making: from circuit elements to emerging principles

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- Ecological decisions depend on fast, flexible, and robust sensory processing
- Raw sensory data are reconfigured into *sensory features* early in processing
- Feature information is routed through parallel pathways that process and recombine features to control distinct actions
- Modulation and shifting brain states tune decision-making to an animal's current demands
- Many questions about how circuits handle mutual feedback with other animals remain open

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Abstract

The interactions an animal has with its prey, predators, neighbors, and competitors are known as ecological interactions. Making effective decisions during these interactions poses fundamental challenges for the nervous system. Among these are the need to filter relevant information out of complex and ever-changing sensory scenes, to balance competing objectives, and to generate robust behavior amid the strong mutual feedbacks that occur during interactions with other animals. Here, I review recent advancements in the study of ecological decision-making. Using research with fishes, I illustrate how knowledge of ethology and brain circuitry are converging to yield a more holistic understanding of how the brain solves these problems to produce robust sequences of natural behavior.

Keywords: decision-making, ecological interactions, explore-exploit, behavioral control, circuits

1 Introduction

2 As we move through the world, we change our behavior based on the
3 sensory stimuli we experience, the physiological states we enter and exit
4 (e.g., hunger, stress), our encounters with other people, and an ever-evolving
5 set of short and longer-term goals. Likewise, following an animal around its
6 natural habitat reveals rich patterns of behavior that include fast and slow
7 transitions among activities, apparent shifts in priorities, and, importantly,

8 diverse interactions with other animals (Fig. 1). The dynamic sequences
9 of behavior we and other animals produce over the course of a day require
10 thousands of decisions. Determining how these decisions are made – both
11 in terms of the behavioral algorithms that map sensory information to one
12 behavioral action or another, and in terms of the properties of neural circuits
13 that control these actions – is at the heart of what it means to understand
14 how the brain generates behavior [1].

15 The past few years have seen a renaissance of interest in ecological decision-
16 making, the process by which animals make decisions during natural inter-
17 actions with prey, predators, neighbors, and competitors. This trend is due,
18 at least in part, to two recent innovations: qualitative leaps in the precision
19 with which the actions of unrestrained animals can be measured [2], and
20 new methods for making in vivo measurements of the nervous system during
21 naturalistic behavior [3, 4, 5, 6, 7, 8]. Here, I review recent advancements in
22 our understanding of ecological decision-making. I focus on studies of fishes,
23 which have served as a model system for researchers seeking to connect neural
24 circuits with sequences of ecologically meaningful behavior.

25 **Parsing sensory scenes and the cocktail party problem**

26 In nature, animals make decisions across an unthinkable broad range of
27 sensory conditions. Across all this variability, an animal must retain the abil-
28 ity to learn about relevant events in the environment such as the approach of
29 a predator or the actions of nearby conspecifics. Doing so involves identify-
30 ing and isolating the stream of sensory data relevant to an event of interest
31 from a complex, dynamic background. This task has been referred to as “the
32 cocktail party problem” [9], in reference to the challenge of focusing on an
33 individual speaker amid the din of a crowded cocktail party. The cocktail
34 party problem is integral to ecological decision-making; without isolating and
35 spatially localizing sensory input from a given source, processes like feedback
36 control for pursuing prey [6, 10, 11] or goal-directed escape responses [12]
37 would be impossible. Through work in fishes, particularly in the visual sys-
38 tem, a picture of how the brain solves this problem is coming into view (Box
39 1).

40 The fish visual system filters sensory scenes through a highly parallelized
41 processing scheme that adjusts to changing statistics of a visual scene on
42 timescales ranging from tens of milliseconds [13] to many minutes [10, 14].
43 The structure of this system reveals two properties likely to be important for

ecological decision-making. First, raw stimulus measurements are reconfigured into *sensory features* early in sensory processing, often within or near the sensory organ itself (Box 1, [13, 15, 16]). Sensory features include things like the size, motion, and patterning of visual objects. Importantly, the dimensionality of feature space is far lower than that of raw visual input space. Computations to determine which features are relevant and which are not begin almost immediately, through the action of distributed microcircuits that make comparisons between sensory features over time and across visual space [13, 15]. The second key property is that sensory features associated with different types of events in the environment are simultaneously processed through distinct pathways in the brain [8]. For example, stimuli associated with prey and stimuli associated with predators are encoded by distinct sets of retinal ganglion cells, and processed through distinct, spatially segregated pathways in the tectum (Box 1, [16]). Processing within these parallel pathways, and competition between them ultimately determine how the animal will respond [4, 15, 17, 18].

Ecological decisions must be made quickly [11], but they must also be robust to complex, dynamic, and often novel sensory scenes. The properties of the fish visual system suggest a strategy by which the brain overcomes these challenges. By computing visual features through distributed circuits in the retina and tectum, information relevant to different types of behavioral actions (e.g. approach or avoid) are extracted simultaneously in a way that maintains sensitivity to novel stimuli as the scene changes [19, 13]. By processing these features through distinct pathways, evidence for different types of ecological events can be accrued rapidly in parallel, compared across pathways, and used to select an action [18].

Balancing competing objectives: from action-selection to changing brain states

Tradeoffs are another ubiquitous feature of ecological decision-making. Tradeoffs in ecological tasks are rarely simple. They often require an animal choose between engaging in very different types of activities, with costs and rewards that are experienced over different time horizons [1]. Selecting the best of a set of alternative actions when feedback is delayed [20], or when different options produce feedback on different timescales is a notoriously challenging problem in machine learning. The fact that animals routinely

79 make such choices during ecological interactions has led to significant interest
80 in this facet of ecological decision-making.

81 **Explore or exploit.** Whether to exploit a known option or to explore
82 other, less familiar options is a common tradeoff faced during decision-making
83 [21]. Marques et al. [7] studied this tradeoff using whole-brain imaging
84 of freely-swimming zebrafish in arenas containing *Paramecium* prey. They
85 found that larvae transition between two behavioral states, termed “explo-
86 ration” and “exploitation,” during which movement and hunting behaviors
87 differ markedly, and brainwide patterns of neural activity are distinct. The
88 exploitation state is strongly correlated with activity of a population of neu-
89 rons in the dorsal raphe nucleus (Box 1 Fig.), and transitions between states
90 are correlated with activity of a trigger network also involving the dorsal
91 raphe, which can become active spontaneously or in response to events such
92 as changing light levels or successful prey capture [7].

93 Another manifestation of the exploration-exploitation tradeoffs occurs
94 within natural hunting sequence themselves. When hunting prey, preda-
95 tors abort a large fraction of pursuits without even attempting to strike prey
96 [22, 23, 10]. In zebrafish, the onset of hunting bouts coincides with elevated
97 activity of neurons in the nucleus isthmi (NI, Box 1 Fig.), a nucleus that
98 reciprocally connects to regions of the optic tectum involved in visual pro-
99 cessing during hunting [23]. The properties of NI connections to the tectum
100 are consistent with the hypothesis that the NI controls sustained hunting
101 behavior by enhancing visually-evoked neural activity in tectal pathways,
102 possibly by enhancing transmission of visual stimuli from RGCs to the optic
103 tectum. One possible function of this is to tune hunting behavior based on
104 an animal’s hunger level. For example, hunger-induced recruitment of tectal
105 neurons that respond to prey-sized moving objects [24] could increase input
106 from the tectum to the NI when an animal is hungry [10]. NI feedback to
107 the optic tectum could then cause hungry animals to extend hunting bouts,
108 as observed in starvation experiments [10].

109 **Feed or flee.** In nature, deciding when to continue feeding and when to
110 flee is a matter of life or death. At the most basic level, balancing this trade-
111 off requires that an animal distinguish food from threats [18], a task that is
112 not always as trivial as it might seem [25]. Larval zebrafish exhibit distinct
113 approach and avoidance behaviors to moving visual objects, and whether the
114 response is positive (approach) or negative (avoid) depends on the object’s
115 size [18, 24]. Interestingly, the relationship between object size and behav-
116 ioral response changes markedly when an animal is hungry. Starved fish

117 approach small objects more frequently and are less likely to avoid objects of
118 intermediate size [24]. This hunger-driven shift in behavioral valence is controlled, in part, by hypothalamic-pituitary-adrenal activity, which modulates
119 size response properties of visually-activated neurons in the optic tectum. In
120 hungry animals, reduced cortisol and enhanced serotonergic transmission promotes recruitment of additional tectal neurons sensitive to small object sizes
121 [24]. This increased activity of tectal neurons may act both by heightening
122 sensitivity to stimuli prey-associated stimuli and by inhibiting a competing
123 pathway involved in avoidance behavior [18].

126 **Perception of risk.** The costs and benefits of making a particular decision depend not only on an animal's internal state but also on the external
127 environment. Changes in decision-making in "risky" versus "safe" environments are widely documented [26]. But if an animal is to modify its behavior
128 based on risk, it needs a way to measure risk. One such measure is the presence of other nearby individuals. Wild coral reef fish feed for shorter periods
129 of time between retreats to shelter when foraging alone than when they forage in large groups [27]. When these animals are exposed to acute threats (looming
130 visual stimuli), responses depend on visual stimuli from the threat *and* visual stimuli produced by neighboring individuals [12]. This implies a mechanism
131 for tuning escape decisions on a fast timescale based on perception of neighboring individuals. How might such context-dependent responses be
132 controlled in the brain? One possibility is that when nearby individuals and other stimuli are viewed at the same time, competition for salience reduces
133 the overall likelihood of responding to any of the stimuli. This could occur, for example, through reciprocal inhibition between competing stimuli within
134 the retina [15].

137 On slower timescales, isolation from conspecifics causes oxytocinergic activity in the hypothalamus [28]. This activity appears to increase activation
138 of premotor neurons in the hindbrain including Mauthner cells (Box 1 Fig.) and other reticulospinal neurons that control motor behavior [29]. Oxytocin-
139 ergic activity is associated with an increase in defensive behaviors and a decrease in feeding, suggesting that social isolation may promote behaviors
140 such as escape responses, but that it also simultaneously suppresses appetite.

143 To make effective decisions, animals must balance tradeoffs. Doing so requires that the animal account for its current needs as well as how its actions
144 will influence the likelihood of different outcomes. The latter is determined at least partly by the state of the environment. A widespread finding is
145 that internal state controls action-selection not simply by favoring one ac-

tion or another in the final stages of decision-making, but also by changing how incoming sensory data are processed [24]. Similar processes may govern changes in decision-making as the state of the environment changes [29, 28]. An important future step will be determining whether these mechanisms for tuning responses are simply crude heuristics, or whether they are based on encodings of the key quantities required to optimally balance tradeoffs: the quantitative values of different outcomes [30], and the probabilities of those outcomes given one action or another [21].

Decision-making and mutual feedbacks

Another characteristic of ecological decision-making is that it often involves strong mutual feedbacks between interacting animals. We have all experienced such feedbacks when trying to avoid colliding with someone walking in the opposite direction on a sidewalk. You veer left and so does your counterpart. You correct right, and so does she. In the presence of a telephone pole or a mailbox, this problem does not arise. Such mutual feedbacks occur during many ecological behaviors including competition for food, hunting mobile prey (Box 2), and, in an extreme form, during social behaviors such as schooling [31] and feeding aggregations [27].

Schooling, aggregations, and feedbacks. Grouping with others has well-documented benefits such as diluting the risk of predation [32], but neighboring individuals also produce large quantities of sensory stimulation [33, 34]. Sensory cues from neighbors can be beneficial [31, 32], but they also create the potential for the actions of an animal to feed back on it through the responses of its neighbors, a process that can be thought of as an extended form of reafference.

Schooling golden shiners (*Notemigonus crysoleucas*) make movement decisions based on the spatial locations of nearby individuals using rules that are consistent with continuous feedback control [35, 36]. By adjusting acceleration, deceleration, and turning based on neighbor locations, animals maintain fairly consistent positions relative to neighbors [35, 37], potentially minimizing the risk of creating strong stimuli that could feed back by producing large changes in neighbor behavior (but see [38]). More recent work suggests that the behavioral algorithms that guide movement decisions in schools can be produced by relatively simple responses to visual stimuli from neighbors [39, 40, 34], that these algorithms change predictably over ontogeny [41, 40, 34], and that they appear to be heritable [40]. A heuristic model of

191 the core computations involved in visual schooling behavior was recently pro-
192 posed [42]. However, the details of how these computations may be carried
193 out in the brain are not yet clear. Interestingly, mutations known to impact
194 other aspects of social behavior also affect how fish transform stimuli from
195 neighbors into movement decisions [40]. These disrupted movement rules
196 alter collective behavior of groups of individuals.

197 In contrast to the behaviors fish employ during routine swimming, the be-
198 havioral algorithms used during behaviors such as collective escape responses
199 can produce strong bursts of sensory stimulation perceptible by neighbors
200 [39, 43]. During collective escapes, one or several individuals in a group
201 typically accelerate [44] creating stimuli that can cause cascades of startle
202 behavior [44, 39, 43]. Notably, the influence of neighbors on any given focal
203 individual are often highly unequal [39, 43], suggesting that some mecha-
204 nism for selectively attending to a dominant neighbor [15, 45] or unequally
205 weighting neighbor stimuli [42] may be important for controlling responses.

206 Many ecological behaviors involve mutual feedbacks (Box 2). In compar-
207 ison to other aspects of decision-making, we know relatively little about how
208 animals control behavior amid such feedbacks. Selective attention [15, 45],
209 behavioral averaging [42], and forecasting future positions of moving tar-
210 gets ([46], Box 2) are candidate mechanisms that could help animals retain
211 behavioral control in these situations. But our understanding of how these
212 mechanisms are implemented in the brain and integrated to produce behavior
213 are far from complete.

214 **Conclusions and Outlook**

215 The current resurgence of interest in ecological behavior is exciting, to
216 be sure. But where will future work on the ethological, computational, and
217 neural aspects of ecological decision-making lead us? Put another way, by
218 studying ecological decision-making, what is it, exactly, that we wish to
219 understand?

220 One answer is that the ability to produce sequences of effective deci-
221 sions across a vast range of novel conditions is among the most conspicuous,
222 yet least understood aspects of natural behavior [1]. By studying ecologi-
223 cal decision-making, we seek principles of brain function that make this si-
224 multaneous flexibility, robustness, and generalizeability possible. Larval fish
225 produce hunting sequences to capture mobile prey within days of hatching

226 [47, 48] even on the first exposure to live prey [49] – a feat tantamount to few-
 227 shot or even zero-shot learning. Likewise, fish respond to novel threat stimuli
 228 by generating escape behaviors that balance competing objectives [15] and
 229 shift seamlessly from one proximate task to another [12] in ways that appear
 230 to sidestep challenges such as constraint violation and catastrophic forgetting
 231 that plague artificial decision-making systems [50, 51]. Here, I have argued
 232 that three general properties of neural circuits help explain how decision-
 233 making in these tasks can be fast, robust, and flexible all at the same time:
 234 distributed computation of sensory features [13, 15], parallel processing of
 235 sets of features by distinct, often competing pathways [8, 16, 18], and slower-
 236 timescale modulation of decision-making circuits based on internal and ex-
 237 ternal states [7, 24, 28]. Are these circuit properties so fundamental that we
 238 should consider them principles of brain organization that enable effective
 239 natural behavior? Further comparative work, as well as targeted computa-
 240 tional studies of these properties could go a long way toward answering this
 241 question.

242 Recent progress notwithstanding, there remains so much to learn about
 243 how animals make ecological decisions. We need principles to help orga-
 244 nize the central challenges involved in ecological tasks, and the mechanisms
 245 by which nervous systems overcome these challenges. This is particularly
 246 true for decisions that involve interactions with other organisms that are,
 247 themselves, sensing and responding. In nature, interacting brains are the
 248 rule rather than the exception [31, 32]. The strategies the nervous system
 249 has evolved to guide decision-making must, therefore, account in some way
 250 for the decisions of other agents with both aligned and conflicting interests.
 251 While related questions have been addressed through work in social psy-
 252 chology, evolutionary game theory, and collective behavior, we still lack an
 253 understanding of the computational principles that allow the brain to pro-
 254 duce dynamic sequences of decisions amid strong mutual feedbacks. Future
 255 studies are poised to change this, opening up a suite of new and exciting ques-
 256 tions whose answers will teach us much about behavior and brain function
 257 alike.

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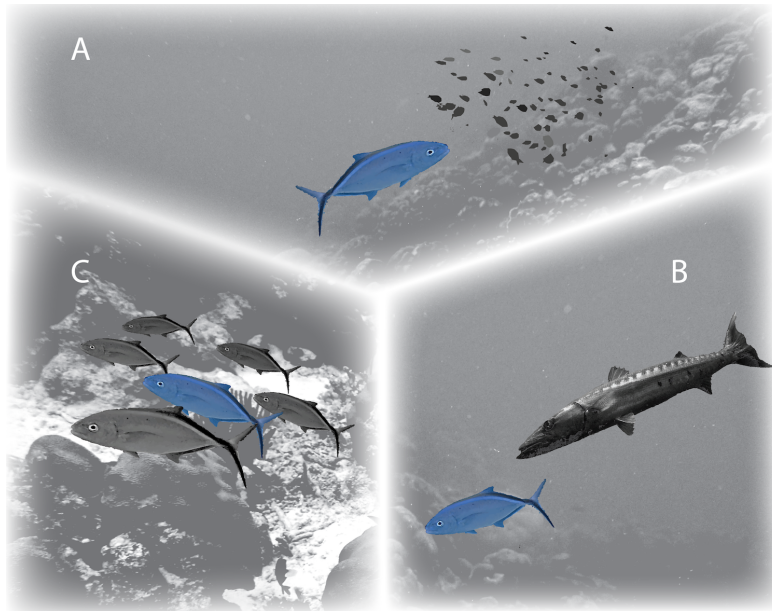


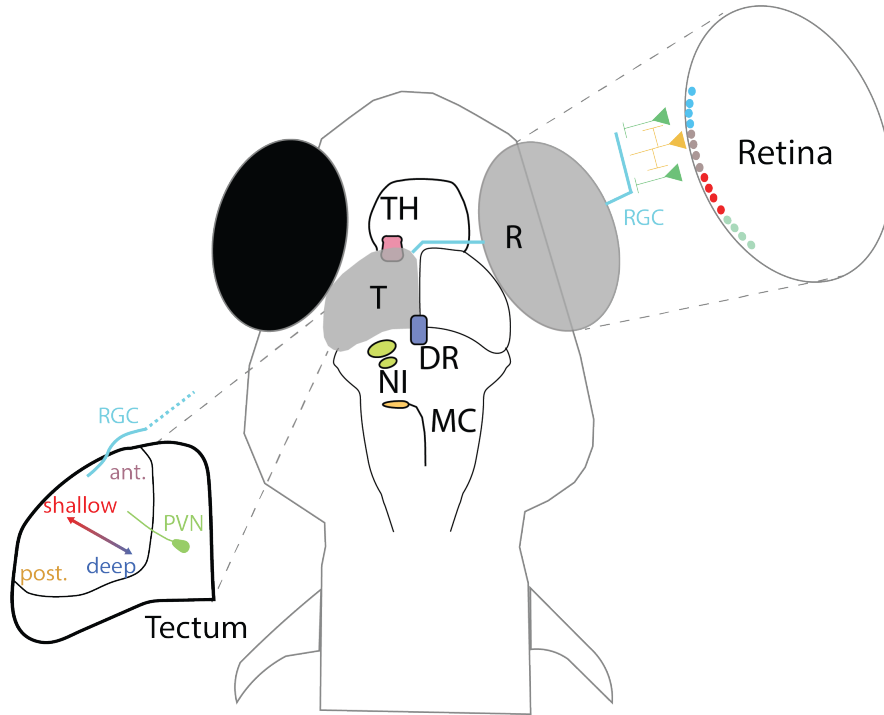
Figure 1: Shifting priorities and sensory demands during ecological decision-making: (A) hunting behavior, (B) predator evasion, (C) social interactions.

263 Boxes

264 *Box 1. Processing and filtration in the fish visual system.*

265 The fish visual system has become a model for understanding how the
266 vertebrate nervous system filters and processes sensory scenes. The first layer
267 of filtration occurs through the spatial organization of sensory receptors. In
268 the fish eye, photoreceptors with distinct spectral sensitivities are heteroge-
269 neously distributed across the retina in ways that are matched to the typical
270 spectral properties of incoming light in different regions of the visual field
271 ([52], Box Fig.). Rather than being transmitted to the brain in raw form,
272 the information captured by receptors is immediately reorganized into sen-
273 sory features, for example, the size, motion speed and direction, and local
274 contrast polarity of a visual object [17, 53]. Cells in the retina also encode
275 larger-scale features such as spatial patterns and changes in such patterns
276 [13].

277 After sensory features are computed, they are transmitted by retinal
278 ganglion cells (RGCs) in parallel to the brain in a fashion that preserves
279 the spatial locations of features [54, 55], but segregates features associated
280 with events that require different kinds of responses into distinct pathways
281 [8, 16, 17, 18, 53, 54] where features are further processed and recombined
282 [53]. In the fish tectum (also known as the superior colliculus), a central
283 relay and processing station for incoming sensory data in the fish midbrain
284 [56], small size- and motion-selective RGCs terminate in superficial tectal
285 layers [16], whereas features associated with expanding objects terminate in
286 deeper tectal layers [57, 16]. Downstream neurons in the tectum integrate
287 feature-selective inputs from multiple RGC types, and in some cases, sharpen
288 specificity for certain object features (e.g. specificity to small moving objects;
289 [16]). Additional modification of tectal processing is provided by other brain
290 regions including the thalamus [5] and hypothalamus [4]. Another stage of
291 filtration occurs in premotor regions in the hindbrain, where recurrent [4] and
292 lateral inhibitory circuit motifs (e.g., between Mauthner cells, [58]) exert ad-
293 ditional control over whether a given stimulus will lead to motor behaviors,
294 and what type of motor response will be executed [59]. Finally, whether
295 an animal responds to a given sequence of stimuli depends on modulation
296 of decision-making circuits on longer timescales, often across multiple brain
297 regions [14, 7].



Elements of the fish visual system showing selected structures and brain regions: eye with Retina (R), Retinal Ganglion Cell (RGC), Tectum (T), Thalamus (TH), Nucleus Isthmi (NI), Dorsal Raphe (DR), and Mauthner Cell (MC). Optic nerve from right eye projects to the left tectum and only brain regions corresponding to that visual hemisphere are shown. Retina inset shows heterogeneous distribution of photoreceptor types across the retina [52] and retinal portion of retinotectal microcircuits, which compute visual features [13] and salience among visual objects [15]. Tectum inset shows RGC projecting to the tectum. Anterior-posterior and shallow-deep axis of tectal neuropil, and preventricular neuron (PVN) are also shown. Anatomy reproduced from [7, 16, 23, 56, 58].

298 *Box 2. Hunting and feedback control*

299 Hunting prey is a an ecological task that requires an animal make a
 300 sequence of decisions – detect prey, initiate pursuit, control pursuit move-
 301 ments, and execute a final strike – to receive a reward. Like larvae of other
 302 fish species [47], larval zebrafish hunt live zooplankton, and this behavior has
 303 become a model for understanding behavioral control [53, 6, 48, 49].

304 Zebrafish hunting bouts follow a characteristic progression. Larvae typi-
 305 cally first respond to prey viewed in the frontal visual field [6, 49, 46]. Follow-
 306 ing prey detection, larvae exhibit characteristic “j-turns” that move the prey

307 toward the proximal, dorsal region of the visual field. This phase of hunt-
 308 ing also involves convergence of the eyes [53], a behavior that increases the
 309 zone of binocular overlap in the proximal region of the visual field. Hunting
 310 sequences end with either an abort [23] or with a terminal attack maneuver
 311 [6, 10, 46]. Larvae typically launch terminal attacks when prey are within
 312 0.4-0.6 mm of the head, near an azimuthal angle of zero, and located slightly
 313 above them in the water column [6, 46], and larvae will dive if necessary to
 314 position prey in this zone [46]. Importantly, hunting behavior requires visual
 315 feedback, and the removal or temporal disruption of this feedback in virtual
 316 prey experiments results in aborted [6] or disrupted [60] hunting sequences.

317 Larval fish face a challenging control problem when hunting fast-moving
 318 prey [47, 6], but strong mutual feedbacks between predator and prey are
 319 even more pronounced during hunting behavior of adult fish. When hunting
 320 evasive prey, predatory bluefish (*Pomatomus saltatrix*) continuously adjust
 321 swimming trajectories as prey move, presumably using visual feedback [61].
 322 Interception trajectories of bluefish are consistent with a strategy known
 323 as “deviated pursuit” in which the pursuer turns continuously to align its
 324 velocity vector with the line-of-sight to the prey plus a small offset angle.
 325 These predators also accelerate to high speeds during the terminal phases of
 326 attacks, possibly in response to evasive maneuvers of prey.

327 Among the primary challenges bluefish and other predators face when
 328 pursuing evasive prey is that posed by sensory-motor delays: the delay be-
 329 tween perception of sensory stimuli and motor responses to those stimuli [62].
 330 Because of such delays, a predator’s movement at any given time is based on
 331 past observations of prey. Computational models of predator-prey pursuit-
 332 evasion interactions suggest that sensory-motor delays are among the most
 333 important constraints limiting the success of predator attacks [11]. One way
 334 for a predator to cope with delays is to steer based on a prediction of fu-
 335 ture prey locations rather than using only currently perceived prey location.
 336 Bolton *et al.* [46] found evidence of such prediction in the hunting maneu-
 337 vers of larval zebrafish, which modulate their steering and acceleration based
 338 not only on the locations of moving prey but also on perceived prey motion.
 339 Forecasting the position of a moving object requires that an animal combine
 340 position and velocity information. Although the fish visual system encodes
 341 variables related to these quantities [53], the neural mechanisms through
 342 which these variables are combined to produce a forecast remain unclear.

343 Recommended reading

344 •• Fernandes *et al.* 2021: This paper explores the circuit-level mechanisms
345 of selective attention in larval zebrafish. The authors report both winner-
346 take-all and averaging strategies implemented in the visual system through
347 retinotectal and isthmotectal circuits, respectively.

348 •• Sosna *et al.* 2019: This paper explores the interaction between indi-
349 vidual behavior and mutual feedback in schools of fish. The authors identify
350 structural changes in the relative positions of fish in a school after exposure
351 to a fear-inducing cue. They show how these changes alter sensory feedbacks
352 among individual animals, thereby modifying group and individual behavior.

353 •• Bolton *et al.* 2019: This paper investigates hunting behavior of larval
354 zebrafish with an emphasis on identifying the behavioral algorithms by which
355 visual input drives movements while hunting fast-moving prey. The authors
356 provide evidence that prey motion in addition to prey position drive action
357 selection, suggesting that larval zebrafish may perform a forecast of future
358 prey positions.

359 •• Marques *et al.* 2020: This paper investigates patterns of whole-brain
360 activity associated with distinct behavioral states. The authors identify two
361 classes of larval zebrafish behavior and find that these correspond to distinct
362 brain states associated with widespread changes in neural activity throughout
363 sensory processing regions. They identify a network of neurons including a
364 population in the dorsal raphe that appears to be involved in triggering
365 changes in state.

366 • Johnston *et al.* 2019: This paper investigates mechanisms for sensitivity
367 to pattern changes in dynamic scenes. The authors identify a class of retino-
368 tectal microcircuits that encodes changes in patterns within a visual scene.
369 They suggest that the simple circuit structure they identify could also serve
370 as a basis for dynamic predictive coding throughout the nervous system.

371 • Wang *et al.* 2020: The authors identify neural populations in the pre-
372 tectum with large receptive fields concentrated on the lower visual field, and
373 populations in the optic tectum selective for small objects in the upper nasal
374 visual field. They provide evidence that pretectal neurons primarily encode
375 large-field optic flow, indicating a distinct parallel channel from that involved
376 in prey perception.

377 • Martin *et al.* 2021: The authors use empirically-calibrated computa-
378 tional model of predator-prey interactions to identify constraints on predator
379 and prey-performance. Their analysis shows that sensory-motor delays fun-

380 damentally constrain predator performance, but not prey performance.

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