

## 62. Neurorobotics: From Vision to Action

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The lay view of a robot is a mechanical human, and thus robotics has always been inspired by attempts to emulate biology. In this Chapter, we extend this biological motivation from humans to animals more generally, but with a focus on the central nervous systems rather than the bodies of these creatures. In particular, we investigate the sensorimotor loop in the execution of sophisticated behavior. Some of these sections concentrate on cases where vision provides key sensory data. Neuroethology is the study of the brain mechanisms underlying animal behavior, and Sect. 62.2 exemplifies the lessons it has to offer robotics by looking at optic flow in bees, visually guided behavior in frogs, and navigation in rats, turning then to the coordination of behaviors and the role of attention. Brains are composed of diverse subsystems, many of which are relevant to robotics, but we have chosen just two regions of the mammalian brain for detailed analysis. Section 62.3 presents the cerebellum. While we can plan and execute actions without a cerebellum, the actions are no longer graceful and become uncoordinated. We reveal how a cerebellum can provide a key ingredient in an adaptive control system, tuning parameters both within and between motor schemas. Section 62.4 turns to the mirror system, which provides shared representations which bridge between the execution of an action and the observation of that action when performed by others. We develop a neurobiological model of how learning may forge mirror neurons for hand

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movements, provide a Bayesian view of a robot mirror system, and discuss what must be added to a mirror system to support robot imitation. We conclude by emphasizing that, while neuroscience can inspire novel robotic designs, it is also the case that robots can be used as embodied test beds for the analysis of brain models.

### 62.1 Definitions

*Neurorobotics* may be defined as *the design of computational structures for robots inspired by the study of the nervous systems of humans and other animals.*

We note the success of *artificial* neural networks – networks of simple computing elements whose connections change with *experience* – as providing a medium for par-

<sup>0</sup> Please check this internal reference

allel adaptive computation that has seen application in robot vision systems and controllers but here we emphasize neural networks derived from the study of specific *neurobiological* systems. Neurorobotics has a twofold aim: creating better machines which employ the principles of natural neural computation; and using the study of bio-inspired robots to improve understanding of the functioning of the brain. Chapter 060<sup>CE0</sup>, *Biologically Inspired Robots*, complements our study of *brain design* with work on *body design*, the design of robotic control and actuator systems based on careful study of the relevant biology.

Walter [62.1] described two *biologically inspired* robots, the electromechanical tortoises *Machina speculatrix* and *M. docilis* (though each body has wheels not legs). *M. speculatrix* has a steerable photoelectric cell, which makes it sensitive to light, and an electrical contact, which allows it to respond when it bumps into obstacles. The photoreceptor rotates until a light of moderate intensity is registered, at which time the organism orients itself towards the light and approaches it. However, very bright lights, material obstacles, and steep gradients are repellent to the *tortoise*. The latter stimuli convert the photoamplifier into an oscillator, which causes alternating movements of butting and withdrawal, so that the robot pushes small objects out of its way, goes around heavy ones, and avoids slopes. The *tortoise* has a *hutch*, which contains a bright light. When the machine's batteries are charged, this bright light is repellent. When the batteries are low, the light becomes attractive to the machine and the light continues to exert an attraction until the tortoise enters the hutch, where the machine's circuitry is temporarily turned off until the batteries are recharged, at which time the bright hutch light again exerts a negative tropism. The second robot, *M. docilis* was produced by grafting onto *M. speculatrix* a circuit designed to form conditioned reflexes. In one experiment, Walter connected this circuit to the obstacle-avoiding device in *M. speculatrix*. Training consisted of blowing a whistle just before bumping the shell.

Although Walter's controllers are simple and not based on neural analysis, they do illustrate an attempt to gain inspiration from seeking the simplest mechanisms that will yield an interesting class of biologically

inspired robot behaviors, and then showing how different additional mechanisms yield a variety of enriched behaviors. *Braitenberg's* book [62.2] is very much in this spirit and has entered the canon of neurorobotics. While their work provides a historical background for the studies surveyed here, we instead emphasize studies inspired by the computational neuroscience of the mechanisms serving vision and action in the human and animal brain. We seek lessons from linking behavior to the analysis of the internal workings of the brain (1) at the relatively high level of characterizing the functional roles of specific brain regions (or the functional units of analysis called schemas Sect. 62.2.4), and the behaviors which emerge from the interactions between them, and (2) at the more detailed level of models of neural circuitry linked to the data of neuroanatomy and neurophysiology. There are lessons for neurorobotics to be learned from even finer-scale analysis of the biophysics of individual neurons and the neurochemistry of synaptic plasticity but these are beyond the scope of this chapter (see *Segev* and *London* [62.3] and *Fregnac* [62.4], respectively, for entry points into the relevant computational neuroscience).

The plan of this Chapter is as follows. After some selected examples from computational neuroethology, the computational analysis of neural mechanisms underlying animal behavior, we show how perceptual and motor schemas and visual attention provide the framework for our action-oriented view of perception, and show the relevance of the computational neuroscience to robotic implementations (Sect. 62.2). We then pay particular attention to two systems of the mammalian brain, the cerebellum and its role in tuning and coordinating actions (Sect. 62.3), and the mirror system and its roles in action recognition and imitation (Sect. 62.4). The extrodution<sup>CE1</sup> will then invite readers to explore the many other areas in which neurorobotics offers lessons from neuroscience to the development of novel robot designs. What follows, then, can be seen as a contribution to the continuing dialogue between robot behavior and animal and human behavior in which particular emphasis is placed on the search for the neural underpinnings of vision, visually guided action, and cerebellar control.

## 62.2 Neuroethological Inspiration

Biological evolution has yielded a staggering variety of creatures, each with brains and bodies adapted to spe-

cific niches. One may thus turn to the neuroethology of specific creatures to gain inspiration for special-purpose

<sup>CE1</sup> Please check this word, which does not appear in standard dictionaries

robots. In Sect. 62.2.1, we will see how researchers have studied bees and flies for inspiration for the design of flying robots, but have also learned lessons for the visual control of terrestrial robots. In Sect. 62.2.2, we introduce *Rana computatrix*, an evolving model of visuomotor coordination in frogs and toads. The name *the frog that computes*, was inspired by Walter's *M. speculatrix* and inspired in turn the names of a number of other *species* of neuroethologically inspired robots, including Beer's [62.5] computational cockroach *Periplaneta computatrix* and Cliff's [62.6] hoverfly *Syrirtta computatrix*.

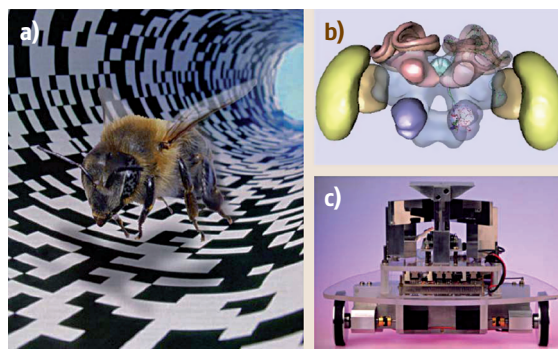
Moreover, we learn not only from the brains of specific creatures but also from comparative analysis of the brains of diverse creatures, looking for homologous mechanisms as computational variants which may then be related to the different ecological niches of the creatures that utilize them. A basic theme of brain evolution is that new functions often emerge through modulation and coordination of existing structures. In other words, to the extent that new circuitry may be identified with the new function, it need not be as a module that computes the function autonomously, but rather as one that can deploy prior resources to achieve the novel functionality. Section 62.2.3 will introduce the role of the rat brain in navigation, while Sect. 62.2.4 will look at the general framework of perceptual schemas motor schemas and coordinated control programs for a high-level view of the neuroscience and neurobotics of vision and action. Finally, Sect. 62.2.5 will look at the control of visual attention in mammals as a homolog of orienting behavior in frogs and toads. All this sets the stage for our emphasis on the roles of the cerebellum (Sect. 62.3) and mirror systems (Sect. 62.4) in the brains of mammals and their implications for neurobotics. We stress that the choice of these two systems is conditioned by our own expertise, and that studies of many other brain systems also hold great importance for neurobotics.

### 62.2.1 Optic Flow in Bees and Robots

Before we turn to vertebrate brains for much of our inspiration for neurobotics, we briefly sample the rich literature on insect-inspired research. Among the founding studies in computational neuroethology were a series of reports from the laboratory of Werner Reichardt in Tübingen which linked the delicate anatomy of the fly's brain to the extraction of visual data needed for flight control. More than 40 years ago, Reichardt [62.7] published a model of motion detection inspired by this work that has long been central to discussions of visual motion

in both the neuroscience and robotics literatures. Borst and Dickinson [62.8] provide a recent study of continuing biological research on visual course control in flies. Such work has inspired a large number of robot studies, including those of van der Smagt and Groen [62.9], Liu and Usseglio-Viretta [62.10], Ruffier et al. [62.11], and Reiser and Dickinson [62.12].

Here, however, we look in a little more detail at honeybees. Srinivasan, Zhang, and Chahl [62.13] continued the tradition of studying image motion cues in insects by investigating how optic flow (the flow of pattern across the eye induced by motion relative to the environment) is exploited by honeybees to guide locomotion and navigation. They analyzed how bees perform a smooth landing on a flat surface: image velocity is held constant as the surface is approached, thus automatically ensuring that flight speed is close to zero at touchdown. This obviates any need for explicit knowledge of flight speed or height above the ground. This landing strategy was then implemented in a robotic gantry to test its applicability to autonomous airborne vehicles. Barron and Srinivasan [62.14] investigated the extent to which ground speed is affected by headwinds. Honey bees were trained to enter a tunnel to forage at a sucrose



**Fig. 62.1a–c** Observation of the trajectories of honeybees flying in visually textured tunnels has provided insights into how bees use optic flow cues to regulate flight speed and estimate distance flown, and balance optic flow in the two eyes to fly safely through narrow gaps. This information has been used to build autonomously navigating robots. (b) schematic illustration of a honey-bee brain, carrying about a million neurons within about one cubic millimeter. (Images courtesy of M. Srinivasan; <sup>CE2</sup> (a) *Science* **287**, 851–853 (2000); (b) *Virtual Atlas of the Honeybee Brain*, <http://www.neurobiologie.fuberlin.de/beebrain/Bee/VRML/SnapshotCosmoall.jpg>. (c) Research School of Biological Sciences, Australian National University)

<sup>CE2</sup> Please provide subfigure captions when available

feeder placed at its far end (Fig. 62.1a). The bees used visual cues to maintain their ground speed by adjusting their airspeed to maintain a constant rate of optic flow, even against headwinds which were, at their strongest, 50% of a bee's maximum recorded forward velocity.

*Vladusich et al.* [62.15] studied the effect of adding goal-defining landmarks. Bees were trained to forage in an optic-flow-rich tunnel with a landmark positioned directly above the feeder. They searched much more accurately when both odometric and landmark cues were available than when only odometry was available. When the two cue sources were set in conflict, by shifting the position of the landmark in the tunnel during tests, bees overwhelmingly used landmark cues rather than odometry. This, together with other such experiments, suggests that bees can make use of odometric and landmark cues in a more flexible and dynamic way than previously envisaged. In earlier studies of bees flying down a tunnel, *Srinivasan and Zhang* [62.16] placed different patterns on the left and right walls. They found that bees balance the image velocities in the left and right visual fields. This strategy ensures that bees fly down the middle of the tunnel, without bumping into the side walls, enabling them to negotiate narrow passages or to fly between obstacles. This strategy has been applied to a corridor-following robot (Fig. 62.1c). By holding constant the average image velocity as seen by the two eyes during flight, the bee avoids potential collisions, slowing down when it flies through a narrow passage. The movement-sensitive mechanisms underlying these various behaviors differ qualitatively as well as quantitatively, from those that mediate the optomotor response (e.g., turning to track a pattern of moving stripes) that had been the initial target of investigation of the Reichardt laboratory. The lesson for robot control is that flight appears to be coordinated by a number of visuo-motor systems acting in concert, and the same lesson can apply to a whole range of tasks which must convert vision to action. Of course, vision is but one of the sensory systems that play a vital role in insect behavior. *Webb* (2001)<sup>TS3</sup> uses her own work on robot design inspired by the auditory control of behavior in crickets to anchor a far-ranging assessment of the extent to which robotics can offer good models of animal behaviors.

### 62.2.2 Visually Guided Behavior in Frogs and Robots

*Lettvin et al.* [62.17] treated the frog's visual system from an ethological perspective, analyzing circuitry in relation to the animal's ecological niche to show that different

cells in the retina and the visual midbrain region known as the tectum were specialized for detecting predators and prey. However, in much visually guided behavior, the animal does not respond to a single stimulus, but rather to some property of the overall configuration. We thus turn to the question *what does the frog's eye tell the frog?*, stressing the embodied nervous system or, perhaps equivalently, an action-oriented view of perception. Consider, for example, the snapping behavior of frogs confronted with one or more fly-like stimuli. *Ingle* [62.18] found that it is only in a restricted region around the head of a frog that the presence of a fly-like stimulus elicits a snap, that is, the frog turns so that its midline is pointed at the stimulus and then lunges forward and captures the prey with its tongue. There is a larger zone in which the frog merely orients towards the target, and beyond that zone the stimulus elicits no response at all. When confronted with two flies within the snapping zone, either of which is vigorous enough that alone it could elicit a snapping response, the frog exhibits one of three reactions: it snaps at one of the flies, it does not snap at all, or it snaps in between at the *average fly*. *Didday* [62.19] offered a simple model of this choice behavior which may be considered as the prototype for a *winner-take-all* (WTA) model which receives a variety of inputs and (under ideal circumstances) suppresses the representation of all but one of them; the one that remains is the *winner* which will play the decisive role in further processing. This was the beginning of *Rana computatrix* (see *Arbib* [62.20, 21] for overviews).

Studies on frog brains and behavior inspired the successful use of potential fields for robot navigation strategies. Data on the strategies used by frogs to capture prey while avoiding static obstacles (*Collett* [62.22]) grounded the model by *Arbib* and *House* [62.23] which linked systems for depth perception to the creation of spatial maps of both prey and barriers. In one version of their model, they represented the map of prey by a potential field with long-range attraction and the map of barriers by a potential field with short-range repulsion, and showed that summation of these fields yielded a field that could guide the frog's detour around the barrier to catch its prey. *Corbacho* and *Arbib* [62.24] later explored a possible role for learning in this behavior. Their model incorporated learning in the weights between the various potential fields to enable adaptation over trials as observed in the real animals. The success of the models indicated that frogs use reactive strategies to avoid obstacles while moving to a goal, rather than employing a planning or cognitive system. Other work (e.g., *Cobas* and *Arbib* [62.25]) studied how the frog's

<sup>TS3</sup> Reference missing

ability to catch prey and avoid obstacles was integrated with its ability to escape from predators. These models stressed the interaction of the tectum with a variety of other brain regions such as the pretectum (for detecting predators) and the tegmentum (for implementing motor commands for approach or avoidance).

Arkin [62.26] showed how to combine a computer vision system with a frog-inspired potential field controller to create a control system for a mobile robot that could successfully navigate in a fairly structured environment using camera input. The resultant system thus enriched other roughly contemporaneous applications of potential fields in path planning with obstacle avoidance for both manipulators and mobile robots (Khatib [62.27]; Krogh and Thorpe [62.28] (1986)). The work on *Rana Computatrix* proceeded at two levels – both biologically realistic neural networks, and in terms of functional units called *schemas*, which compete and cooperate to determine behavior. Section 62.2.4 will show how more general behaviors can emerge from the competition and cooperation of perceptual and motor schemas as well as more abstract coordinating schemas too. Such ideas were, of course, developed independently by a number of authors, and so entered the robotics literature by various routes, of which the best known may be the subsumption architecture of Brooks [62.28] and the ideas of Braitenberg cited above, whereas Arkin's work on behavior-based robotics [62.29] is indeed rooted in schema theory. Arkin et al. [62.30] present a recent example of the continuing interaction between robotics and ethology, offering a novel method for creating high-fidelity models of animal behavior for use in robotic systems based on a behavioral systems approach (i. e., based on a schema-level model of animal behavior, rather than analysis of biological circuits in animal brains), and describe how an ethological model of a domestic dog can be implemented with AIBO, the Sony entertainment robot.

### 62.2.3 Navigation in Rat and Robot

The tectum, the midbrain visual system which determines how the frog turns its whole body towards its prey or orients it for escape from predators (Sect. 62.2.2), is homologous with the superior colliculus of the mammalian midbrain. The rat superior colliculus has been shown to be *frog-like*, mediating approach and avoidance (Dean et al. [62.31]), whereas the best-studied role of the superior colliculus of cat, monkey, and human is in the control of saccades, rapid eye movements to acquire a visual target. Moreover, the superior colliculus

can integrate auditory and somatosensory information into its visual frame (Stein and Meredith [62.32]) and this inspired Strosslin et al. [62.33] to use a biologically inspired approach based on the properties of neurons in the superior colliculus to learn the relation between visual and tactile information in control of a mobile robot platform. More generally, then, the comparative study of mammalian brains has yielded a rich variety of computational models of importance in neurobotics. In this section, we further introduce the study of *mammalian neurobotics* by looking at studies of mechanisms of the rat brain for spatial navigation.

The frog's detour behavior is an example of what O'Keefe and Nadel [62.34] called the *taxon (behavioral orientation) system* [as in Braitenberg, [62.35] a *taxis* (plural *taxes*) is an organism's response to a stimulus by movement in a particular direction]. They distinguished this from a system for *map-based navigation*, and proposed that the latter resides in the hippocampus, though Guazzelli et al. [62.36] qualified this assertion, showing how the hippocampus may function as *part of* a cognitive map. The taxon versus map distinction is akin to the distinction between reactive and deliberative control in robotics (Arkin et al. [62.30]). It will be useful to relate taxis to the notion of an *affordance* (Gibson [62.37]), a feature of an object or environment relevant to action, for example, in picking up an apple or a ball, the identity of the object may be irrelevant, but the size of the object is crucial. Similarly, if we wish to push a toy car, recognizing the make of car copied in the toy is irrelevant, whereas it is crucial to recognize the placement of the wheels to extract the direction in which the car can be readily pushed. Just as a rat may have basic taxes for approaching food or avoiding a bright light, say, so does it have a wider repertoire of affordances for possible actions associated with the immediate sensing of its environment. Such affordances include *go straight ahead* for visual sighting of a corridor, *hide* for a dark hole, *eat* for food as sensed generically, *drink* similarly, and the various turns afforded by, e.g., the sight of the end of the corridor. It also makes rich use of olfactory cues. In the same way, a robot's behavior will rely on a host of reactions to local conditions in fulfilling a plan, e.g., knowing that it must go to the end of a corridor it will nonetheless use local visual cues to avoid hitting obstacles, or to determine through which angle to turn when reaching a bend in the corridor.

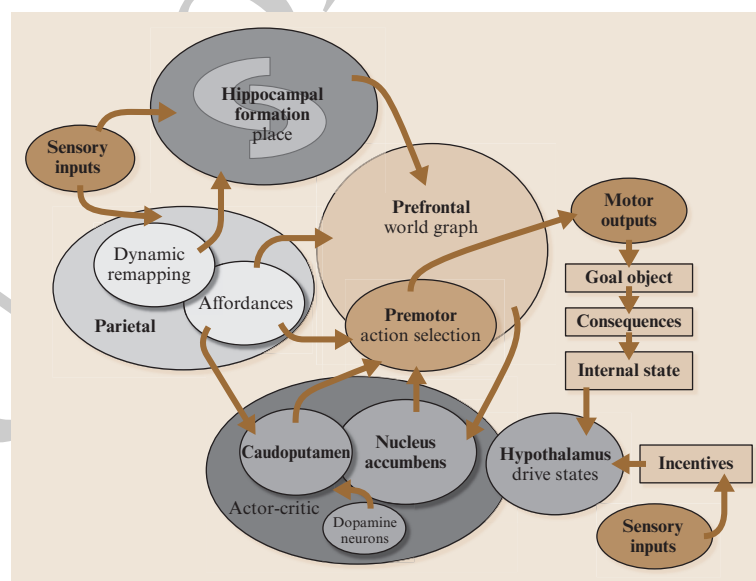
Both normal and hippocampal-lesioned rats can learn to solve a simple T-maze (e.g., learning whether to turn left or right to find food) in the absence of any consistent environmental cues other than the T-shape of

the maze. If anything, the lesioned animals learn this problem faster than normals. After the criterion was reached, probe trials with an eight-arm radial maze were interspersed with the usual T-trials. Animals from both groups consistently chose the side to which they were trained on the T-maze. However, many did not choose the 90° arm but preferred either the 45° or 135° arm, suggesting that the rats eventually solved the T-maze by learning to rotate within an egocentric orientation system at the choice point through *approximately* 90°. This leads to the hypothesis of an *orientation vector* being stored in the animal's brain but does not tell us where or how the orientation vector is stored. One possible model would employ coarse coding in a linear array of cells, coding for turns from -180° to +180°. From the behavior, one might expect that only the cells close to the preferred *behavioral* direction are excited, and that learning *marches* this peak from the old to the new preferred direction. To *unlearn* -90°, say, the array must reduce the peak there, while at the same time *building* a new peak at the new direction of +90°. If the old peak has *mass*  $p(t)$  and the new peak has *mass*  $q(t)$ , then as  $p(t)$  declines toward 0 while  $q(t)$  increases steadily from 0, the center of mass will progress from -90° to +90°, fitting the behavioral data.

The determination of movement direction was modeled by *rat-ification* of the *Arbib* and *House* [62.23] model of frog detour behavior. There, prey was represented by excitation coarsely coded across a population, while barriers were encoded by inhibition whose ex-

tent closely matched the retinotopic extent of each barrier. The sum of excitation was passed through a winner-takes-all circuit to yield the choice of movement direction. As a result, the direction of the gap closest to the prey, rather than the direction of the prey itself, was often chosen for the frog's initial movement. The same model serves for behavioral orientation once we replace the direction of the prey (frog) by the direction of the orientation vector (rat), while the barriers correspond to the presence of walls rather than alley ways.

To approach the issue of how a cognitive map can extend the capability of the affordance system, *Guazzelli et al.* [TS<sup>5</sup>] extended the *Lieblich* and *Arbib* [62.39] approach to building a cognitive map as a *world graph*, a set of nodes connected by a set of edges, where the nodes represent recognized places or situations, and the links represent ways of moving from one situation to another. A crucial notion is that a place encountered in different circumstances may be represented by multiple nodes, but that these nodes may be merged when the similarity between these circumstances is recognized. They model the process whereby the animal decides where to move next, on the basis of its current drive state (hunger, thirst, fear, etc.). The emphasis is on spatial maps for guiding locomotion into regions not necessarily currently visible, rather than retinotopic representations of immediately visible space, and yields exploration and latent learning without the introduction of an explicit exploratory drive. The model shows: (1) how a route, possibly of



**Fig. 62.2** The TAM-WG<sup>CE4</sup> model has at its basis a system, TAM, for exploiting affordances. This is elaborated by a system, WG, which can use a cognitive map to plan paths to targets which are not currently visible. Note that the model processes two different kinds of sensory inputs. At the *bottom right* are those associated with, e.g., hypothalamic systems for feeding and drinking, and that may provide both incentives and rewards for the animal's behavior, contributing both to behavioral choices, and to the reinforcement of certain patterns of behavior. The nucleus accumbens and caudo-putamen mediate an actor-critic style of reinforcement learning based on the hypothalamic drive of the dopamine system. The sensory inputs at the *top left* are those that allow the

<sup>CE4</sup> Please define this abbreviation on first use  
<sup>TS5</sup> There is no reference. Is this OK?

many steps, may be chosen that leads to the desired goal; (2) how short cuts may be chosen; and (3) through its account of node merging why, in open fields, place cell firing does not seem to depend on direction.

The overall structure and general mode of operation of the complete model is shown in Fig. 62.2, which gives a vivid sense of the lessons to be learned by studying not only specific systems of the mammalian brain but also their patterns of large-scale interaction. This model is but one of many inspired by the data on the role of the hippocampus and other regions in rat navigation. Here, we just mention as pointers to the wider literature the papers by Girard et al. [62.41] and Meyer et al. [62.42], which are part of the *Psikharpax* project, which is doing for rats what *Rana computatrix* did for frogs and toads.

#### 62.2.4 Schemas and Coordinated Control Programs

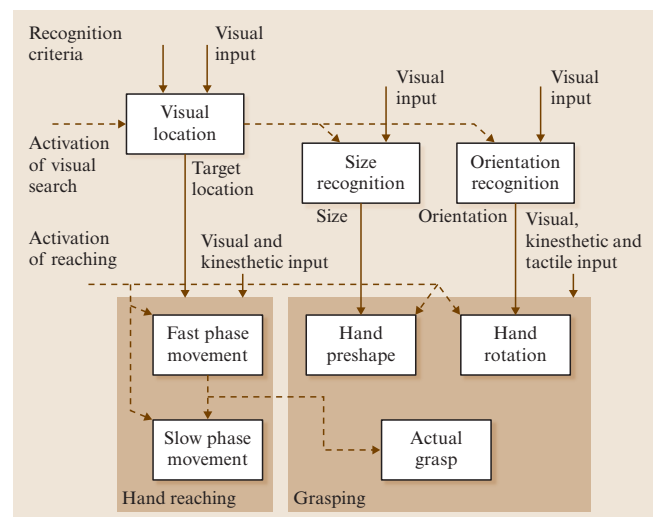
Schema theory complements neuroscience's well-established terminology for levels of *structural* analysis (brain region, neuron, synapse) with a *functional* vocabulary, a framework for analysis of behavior with no necessary commitment to hypotheses on the localization of each *schema* (unit of functional analysis), but which can be linked to a structural analysis whenever appropriate. Schemas provide a high-level vocabulary which can be shared by brain theorists, cognitive scientists, connectionists, ethologists, kinesiologists – and roboticists. In particular, schema theory can provide a distributed programming environment for robotics [see, e.g., the robots schemas (RS) language of Lyons and Arbib [62.43], and supporting architectures for distributed control as in Metta et al. [62.44]]. Schema theory becomes specifically relevant to *neurorobotics* when the schemas are inspired by a model constrained by data provided by, e.g., human brain mapping, studies of the effects of brain lesions, or neurophysiology.

A *perceptual schema* not only determines whether an object or other *domain of interaction* is present in the environment but can also provide important <sup>CE6</sup>. The activity level of a perceptual schema signals the credibility of the hypothesis that what the schema represents is indeed present, whereas other schema parameters represent relevant properties such as size, location, and motion of the perceived object. Given a perceptual schema we may need several schema instances, each suitably tuned, to subservise perception of several instances of its domain, e.g., several chairs in a room.

*Motor schemas* provide the control systems which can be coordinated to affect a wide variety of actions.

The activity level of a motor schema instance may signal its *degree of readiness* to control some course of action. What distinguishes schema theory from usual control theory is the transition from emphasizing a few basic controllers (e.g., for locomotion or arm movement) to a large variety of motor schemas for diverse skills (peeling an apple, climbing a tree, changing a light bulb), with each motor schema depending on perceptual schemas to supply information about objects which are targets for interaction. Note the relevance of this for robotics – the robot needs to know not only *what* the object is but also *how* to interact with it. Modern neuroscience (see the works by Ungerleider and Mishkin [62.45] and Goodale and Milner [62.46]) has indeed established that the monkey and human brain each use a dorsal pathway (via the parietal lobe) for the *how* and a ventral pathway (via the inferotemporal cortex) for the *what*. Moreover, coupling between these two *streams* mediates their integration in normal ongoing behavior.

A *coordinated control program* interweaves the activation of various perceptual, motor, and coordinating schemas in accordance with the current task and sensory environment to mediate complex behaviors. Figure 62.3 shows the original coordinated control program (Arbib [62.40]), inspired by the data of Jeannerod and



**Fig. 62.3** Hypothetical coordinated control program for reaching and grasping. The perceptual schemas (*top*) provide parameters for the motor schemas (*bottom*) for the control of *reaching* (arm transport  $\approx$  g and reaching) and *grasping* (controlling the hand to conform to the object). Dashed lines indicate activation signals which establish timing relations between schemas; solid lines indicate transfer of data. (After Arbib [62.40])

<sup>CE6</sup> Please complete this sentence fragment

*Biguer* [62.47]). As the hand moves to grasp a ball, it is *reshaped* so that, when it has almost reached the ball, it is of the right shape and orientation to enclose some part of the ball prior to gripping it firmly. The outputs of three perceptual schemas are available for the concurrent activation of two motor schemas, one controlling the arm to transport the hand towards the object and the other reshaping the hand. Once the hand is reshaped, it is only the completion of the fast initial phase of hand transport that *wakes up* the final stage of the grasping schema to shape the fingers under control of tactile feedback. [This model anticipates the much later discovery of perceptual schemas for grasping in a localized area (AIP) of parietal cortex and motor schemas for grasping in a localized area (F5) of premotor cortex; see Fig. 62.4.] The notion of schema is thus *recursive* – a schema may be analyzed as a coordinated control program of finer schemas, and so on until such time as a secure foundation of neural specificity is attained.

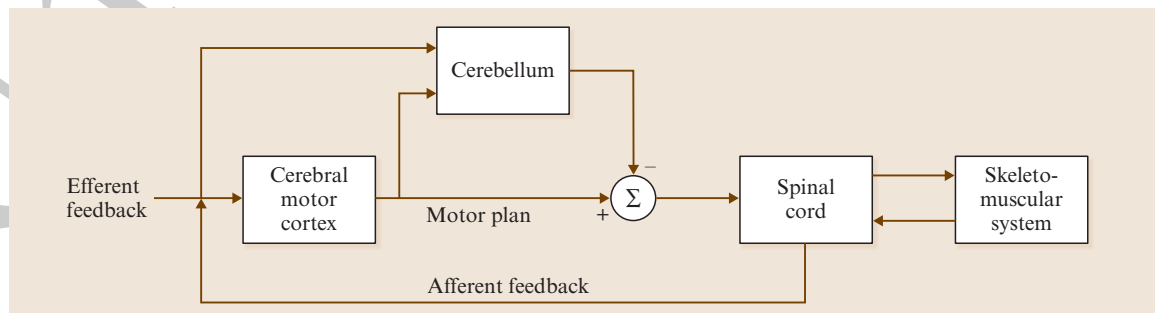
Subsequent work has refined the scheme of Fig. 62.3, for example, *Hoff* and *Arbib*'s [62.48] model uses the *time needed for completion* of each of the movements – transporting the hand and reshaping the hand – to explain data on how the reach to grasp responds to perturbation of target location or size. Moreover, *Hoff* and *Arbib* [62.49] show how to embed an optimality principle for arm trajectories into a controller which can use feedback to resist noise and compensate for target perturbations, and a predictor element to compensate for delays from the periphery. The result is a feedback system which can *act like* a feedforward system described by the optimality principle in *familiar* situations, where the conditions of the desired behavior are not perturbed and accuracy requirements are such that *normal* errors in execution may be ignored. However, when perturbations must be corrected for or when great precision is required, feedback plays a crucial role in keeping the

behavior close to that desired, taking account of delays in putting feedback into effect. This integrated view of feedback and feedforward within a single motor schema seems to us of value for neurorobotics as well as the neuroscience of motor control.

It is standard to distinguish a *forward* or *direct* model which represents the path from motor command to motor output, from the *inverse* model which models the reverse pathway, i. e., going from a desired motor outcome to a set of motor commands likely to achieve it. As we have just suggested, the action plan unfolds *as if* it were feedforward or open-loop when the actual parameters of the situation match the stored parameters, while a feedback component is employed to counteract disturbances (current feedback) and to learn from mistakes (learning from feedback). This is obtained by relying on a forward model that predicts the outcome of the action as it unfolds in real time. The accuracy of the forward model can be evaluated by comparing the output generated by the system with the signals derived from sensory feedback (*Miall* et al. [62.50]). Also, delays must be accounted for to address the different propagation times of the neural pathways carrying the predicted and actual outcome of the action. Note that the forward model in this case is relatively simple, predicting only the motor output in advance: since motor commands are generated internally it is easy to imagine a predictor for these signals (known as an efference copy). The inverse model, on the other hand, is much more complicated since it maps sensory feedback (e.g., vision) back into motor terms. These concepts will prove important both in our study of the cerebellum (Sect. 62.3) and mirror systems (Sect. 62.4).

### 62.2.5 Saliency and Visual Attention

Discussions of how an animal (or robot) grasps an object assume that the animal or robot is attending to the



**Fig. 62.4** Simplified control loop relating cerebellum and cerebral motor cortex in supervising the spinal cord's control of the skeleto-muscular system



relevant object. Thus, whatever the subtlety of processing in the canonical and mirror systems for grasping, its success rests on the availability of a visual system coupled to an oculomotor control system that bring foveal vision to bear on objects to set parameters needed for successful interaction. Indeed, the general point is that attention greatly reduces the processing load for animal and robot. The catch, of course, is that reducing computing load is a Pyrrhic victory unless the moving focus of attention captures those aspects of behavior relevant for the current task – or supports necessary *priority interrupts*. Indeed, directing attention appropriately is a topic for which there is a great richness of both neurophysiological data and robotic application (see *Deco* and *Rolls* [62.51] and *Choi*, et al. [62.38]).

In their neuromorphic model of the bottom-up guidance of attention in primates, *Itti* and *Koch* [62.52] decompose the input video stream into eight feature channels at six spatial scales. After surround suppression, only a sparse number of locations remain active in each map, and all maps are combined into a unique *saliency map*. This map is scanned by the focus of attention in order of decreasing saliency through the interaction between a winner-takes-all mechanism (which selects the most salient location) and an *inhibition-of-return* mechanism (which transiently suppresses recently attended locations from the saliency map). Because it includes a detailed low-level vision front-end, the model has been applied not only to laboratory stimuli, but also to a wide variety of natural scenes, predicting a wealth of data from psychophysical experiments.

When specific objects are searched for, low-level visual processing can be biased both by the gist (e.g., *outdoor suburban scene*) and also for the features of that object. This top-down modulation of bottom-up processing results in an ability to guide search towards targets of interest (*Wolfe* [62.53]). Task affects eye movements (*Yarbus* [62.54]), as do training and general expertise. *Navalpakkam* and *Itti* [62.55] propose a computational model which emphasizes four aspects that are important in biological vision: deter-

mining the task relevance of an entity, biasing attention for the low-level visual features of desired targets, recognizing these targets using the same low-level features, and incrementally building a visual map of task relevance at every scene location. It attends to the most salient location in the scene, and attempts to recognize the attended object through hierarchical matching against object representations stored in long-term memory. It updates its working memory with the task relevance of the recognized entity and updates a topographic task-relevance map with the location and relevance of the recognized entity, for example, in one task the model forms a map of likely locations of cars from a video clip filmed while driving on a highway. Such work illustrates the continuing interaction between models based on visual neurophysiology and human psychophysics with the tackling of practical robotic applications.

*Orabona* et al. [62.56] implemented an extension of the *Itti–Koch* model on a humanoid robot with moving eyes, using log-polar vision as in *Sandini* and *Tagliasco* [62.57], and changing the feature construction pyramid by considering proto-object elements (blob-like structures rather than edges). The inhibition-of-return mechanism has to take into account a moving frame of reference, the resolution of the fovea is very different from that at the periphery of the visual field, and head and body movements need to be stabilized. The control of movement might thus have a relationship with the structure and development of the attention system. *Rizzolatti* et al. [62.58] proposed a role for the feedback projections from premotor cortex to the parietal lobe, assuming that they form a tuning signal that dynamically changes visual perception. In practice this can be seen as an implicit attention system which *selects* sensory information while the action is being prepared and subsequently executed (see *Flanagan* and *Johansson* [62.59], *Flanagan* et al. [62.60], and *Mataric* and *Pomplun* [62.61]). The early responses, before action onset, of many premotor and parietal neurons suggest a premotor mechanism of attention that deserves exploration in further work in neurobotics.

## 62.3 The Role of the Cerebellum

Although cerebellar involvement in muscle control was advocated long ago by the Greek gladiator surgeon Galen of Pergamum (129–216/17 CE), it was the publication by *Eccle* et al. [62.62] of the first comprehensive

account of the detailed neurophysiology and anatomy of the cerebellum (*Ito* [62.63]) that provided the inspiration for the Marr–Albus model of cerebellar plasticity (*Marr* [62.64]; *Albus* [62.65]) that is at the heart of

most current modeling of the role of the cerebellum in control of motion and sensing. From a robotics point of view, the most convincing results are based on *Albus'* [62.66] cerebellar model articulation controller (CMAC) model and subsequent implementations by *Miller* [62.67]. These models, however, are only remotely based on the structure of the biological cerebellum. More detailed models are usually only applied to two-degree-of-freedom robotic structures, and have not been generalized to real-world applications (see *Peters* and *van der Smagt* [62.68]). The problem may lie with viewing the cerebellum as a stand-alone dynamics controller. An important observation about the brain is that schemas are widely distributed, and different aspects of the schemas are computed in different parts of the brain. Thus, one view is that (1) the cerebral cortex has the necessary models for choosing appropriate actions and getting the general shape of the trajectory assembled to fit the present context, whereas (2) the cerebellum provides a side-path which (on the basis of extensive learning of a forward motor model) provides the appropriate corrections to compensate for control delays, muscle nonlinearities, Coriolis and centrifugal forces occasioned by joint interactions, and subtle adjustments of motor neuron firing in simultaneously active motor pattern generators to ensure their smooth coordination. Thus, for example, a patient with cerebellar lesions may be able to move his arm to successfully reach a target, and to successfully adjust his hand to the size of an object. However, he lacks the machinery to perform either action both swiftly and accurately, and further lacks the ability to coordinate the timing of the two subactions. His behavior will thus exhibit *decomposition of movement* – he may first move the hand till the thumb touches the object, and only then shape the hand appropriately to grasp the object. Thus analysis of how various components of cerebral cortex interact to support forward and inverse models which determine the *overall shape of the behavior* must be complemented by analysis of how the cerebellum handles control delays and nonlinearities to transform a well-articulated plan into graceful coordinated action. Within this perspective, cerebellar structure and function will be very helpful in the control of a new class of highly antagonistic robotic systems as well as in adaptive control.

### 62.3.1 The Human Control Loop

Lesions and deficits of the cerebellum impair the coordination and timing of movements while introducing

excessive, undesired motion: effects which cannot be compensated by the cerebral cortex. According to mainstream models, the cerebellum filters descending motor cortex commands to cope with timing issues and communication delays which go up to 50 ms one way for arm control. Clearly, closed-loop control with such delays is not viable in any reasonable setting, unless augmented with an open-loop component, predicting the behavior of the actuator system. This is where the cerebellum comes into its own. The complexity of the vertebrate musculoskeletal system, clearly demonstrated by the human arm using a total of 19 muscle groups for planar motion of the elbow and shoulder alone (see *Nijhof* and *Kouwenhoven* [62.69]) requires a control mechanism coping with this complexity, especially in a setting with long control delays. One cause for this complexity is that animal muscles come in antagonistic pairs (e.g., flexing versus extending a joint). Antagonistic control of muscle groups leads to energy-optimal (*Damsgaard et al.* [62.70]) and intrinsically flexible systems. Contact with stiff or fast-moving objects requires such flexibility to prevent breakage. In contrast, classical (industrial) robots are stiff, with limb segments controlled by linear or rotary motors with gear boxes. Even so, most laboratory robotic systems have passively stiff joints, with active joint flexibility obtainable only by using fast control loops and joint torque measurement. Although it may be debatable whether such robotic systems require cerebellar-based controllers, the steady move of robotics towards complete anthropomorphism by mimicking human (hand and arm) kinematics as well as dynamics as closely as possible, requires the search for alternative, neuromorphic control solutions.

Vertebrate motor control involves the cerebral motor cortex, basal ganglia, thalamus, cerebellum, brain stem, and spinal cord. Motor programs, originating in the cortex, are fed into the cerebellum. Combined with sensory information through the spinal cord, it sends motor commands out to the muscles via the brain stem and spinal cord, which controls muscle length and joint stiffness (see *Bullock* and *Contreras-Vidal* [62.71]). The full control loop is depicted in Fig. 62.4 (see *Schaal* and *Schweighofer* [62.72], for an overview of robotic versus brain control loops). The model in Fig. 62.4 clearly resembles the well-known computed torque model and, when the cerebellum is interpreted as a Smith model, it serves to cope with long delays in the control loop (see *Miall et al.* [62.50] and *van der Smagt* and *Hirzinger* [62.73]). It is thus understood to incorporate a forward model of the skeletomuscular system.

Purkinje cell (PC)  
 Mossy fiber (MF)  
 microzone  
 microcomplex  
 climbing fiber (CF)  
 olive  
 basket cell  
 Golgi cell

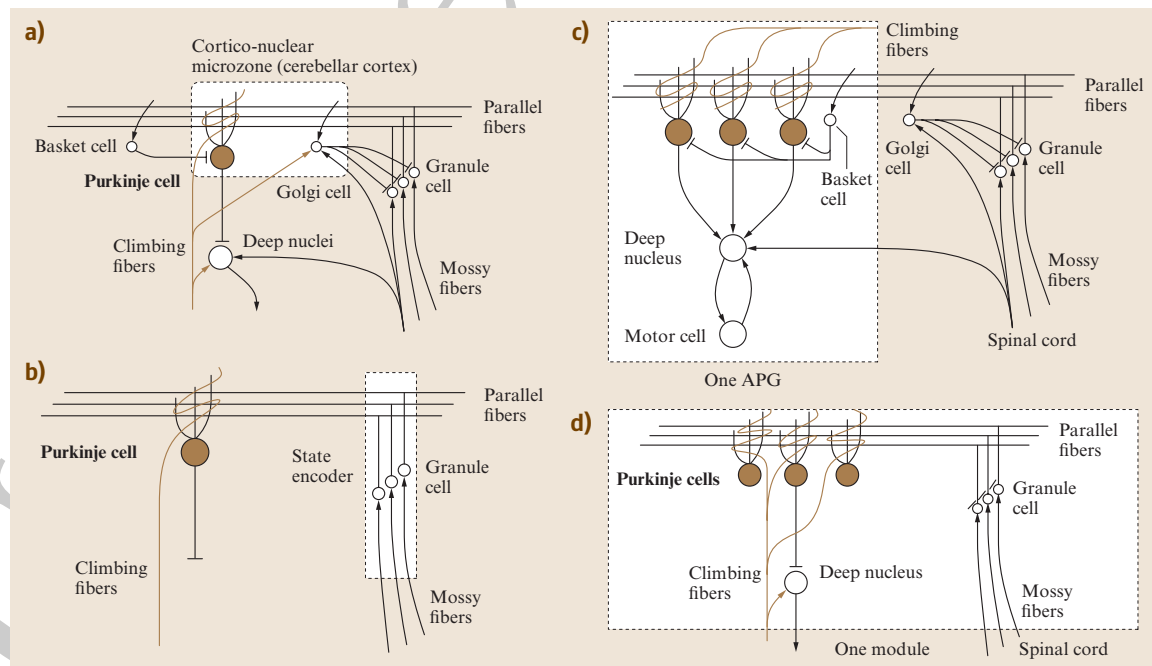
Index entries on this page

Alternative approaches use the cerebellum as an inverse model (see *Ebadzadeh et al. [62.74]*), which however leads to increased complexity and control loop stability problems.

### 62.3.2 Models of Cerebellar Control

The cerebellum can be divided into two parts: the cortex and the deep nuclei. There are two systems of fibers bringing input to the both the cortex and nuclei: the mossy fibers and the climbing fibers. The only output from the cerebellar nucleus comes from cells called Purkinje cells, and they project only to the cerebellar nuclei, where their effect is inhibitory. This inhibition sculpts the output of the nuclei which (the effect varies from nucleus to nucleus) may act by modulating activity in the spinal cord, the mid-brain or the cerebral cortex. We now turn to models which make explicit use of the cellular structure of the *cerebellar cortex* (see *Ecclès et al. [62.62]* and *Ito [62.75]*, and also Fig. 62.5a). The human cerebellum has 7–14 million Purkinje cells (PCs), each receiving about 200 000 synapses. Mossy

fibers (MFs) arise from the spinal cord and brainstem. They synapse onto granule cells and deep cerebellar nuclei. Granule cells have axons which each project up to form a T, with the bars of the T forming the parallel fibers (PFs). Each PF synapses on about 200 PCs. The PCs, which are grouped into microzones, inhibit the deep nuclei. PCs with their target cells in cerebellar nuclei are grouped together in microcomplexes (see *Ito [62.75]*). Microcomplexes are defined by a variety of criteria to serve as the units of analysis of cerebellar influence on specific types of motor activity. The climbing fibers (CF) arise from the inferior olive. Each PC receives synapses from only one CF, but a CF makes about 300 excitatory synapses on each PC which it contacts. This powerful input alone is enough to fire the PC, though most PC firing depends on subtle patterns of PF activity. The cerebellar cortex also contains a variety of inhibitory interneurons. The basket cell is activated by PF afferents and makes inhibitory synapses onto PCs. Golgi cells receive input from PFs, MFs, and CFs and inhibit granule cells.



**Fig. 62.5** (a) Major cells in the cerebellum. (b) Cells in the Marr–Albus model. The granule cells are state encoders, feeding system state, and sensor data into the PC. PC/PF synapses are adjusted using the Widrow–Hoff rule. The output of the PC are steering signals for the robotic system. (c) The APG model, using the same state encoder as (b). (d) The MPPFIM model. A single module corresponds to a group of Purkinje cells: predictor, controller, and responsibility estimator. The granule cells generate the necessary basis functions of the original information

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### The Marr–Albus Model

In the Marr–Albus model (see *Marr* [62.64] and *Albus* [62.65]) the cerebellum functions as a classifier of sensory and motor patterns received through the MFs. Only a small fraction of the parallel fibers (PF) are active when a Purkinje cell (PC) fires and thus influence the motor neurons. Both Marr and Albus hypothesized that the error signals for improving PC firing in response to PF, and thus MF input, were provided by the climbing fibers (CF), since only one CF affects a given PC. However, Marr hypothesized that CF activity would strengthen the active PF/PC synapses using a Widrow–Hoff learning rule, whereas Albus hypothesized they would weaken them. This is an important example of a case where computational modeling inspired important experimentation. Eventually, Masao Ito was able to demonstrate that Albus was correct – the weakening of active synapses is now known to involve a process called long-term depression (*Ito* [62.75]). However, the rule with weakening of synapses still known as the Marr–Albus model, and remains the reference model for studies of synaptic plasticity of cerebellar cortex. However, both Marr and Albus viewed each PC as functioning as a perceptron whose job it was to control an elemental movement, contrasting with more plausible models in which PCs serve to modulate the involvement of microcomplexes (which include cells of the deep nuclei) in motor pattern generators (e.g., the APG model described below).

Since the development of the Marr–Albus model several cerebellar models have been introduced in which cerebellar plasticity plays a key role. Limiting our overview to computational models, we will describe (1) the cerebellar model articulation controller (CMAC), (2) the adjustable pattern generator (APG), (3) the Schweighofer–Arbib model, and (4) the multiple paired forward-inverse models (see *van der Smagt* [62.76,77]).

### The Cerebellar Model Articulation Controller (CMAC)

One of the first well-known computational models of the cerebellum is the CMAC (*Albus* [62.66]; see Fig. 62.5b). The algorithm was based on Albus' understanding of the cerebellum, but it was not proposed as a biologically plausible model. The idea has its origins in the BOXES approach, in which for  $n$  variables an  $n$ -dimensional hypercube stores function values in a lookup table. BOXES suffers from the curse of dimensionality: if each variable can be discretized into  $D$  different steps, the hypercube has to store  $D^n$  function values in memory. Albus

assumed that the mossy fibers provided discretized function values. If the signal on a mossy fiber is in the receptive field of a particular granule cell, it fires onto a parallel fiber. This mapping of inputs onto binary output variables is often considered to be the generalization mechanism in CMAC. The learning signals are provided by the climbing fibers.

Albus' CMAC can be described in terms of a large set of overlapping, multidimensional receptive fields with finite boundaries. Every input vector falls within the range of some local receptive fields. The response of CMAC to a given input is determined by the average of the responses of the receptive fields excited by that input. Similarly, the training for a given input vector affects only the parameters of the excited receptive fields.

The organization of the receptive fields of a typical Albus CMAC with a two-dimensional input space can be described as follows. The set of overlapping receptive fields is divided into  $C$  subsets, commonly referred to as *layers*. Any input vector excites one receptive field from each layer, for a total of  $C$  excited receptive fields for any input. The overlap of the receptive fields produces input generalization, while the offset of the adjacent layers of receptive fields produces input quantization. The ratio of the width of each receptive field (input generalization) to the offset between adjacent layers of receptive fields (input quantization) must be equal to  $C$  for all dimensions of the input space. This organization of the receptive fields guarantees that only a fixed number,  $C$ , of receptive fields is excited by any input.

If a receptive field is excited, its response equals the magnitude of a single adjustable weight specific to that receptive field. The CMAC output is the average of the weights of the excited receptive fields. If nearby points in the input space excite the same receptive fields, they produce the same output value. The output only changes when the input crosses one of the receptive field boundaries. The Albus CMAC thus produces piecewise-constant outputs. Learning takes place as described above.

CMAC neural networks have been applied in various control situations *Miller* [62.67], starting from adaptation of PID control parameters for an industrial robot arm and hand–eye systems up to biped walking (see *Sabourin* and *Bruneau* [62.78]).

### The Adjustable Pattern Generator APG

The APG model (*Houk* et al. [62.79]) got its name because the model can generate a burst command with adjustable intensity and duration. The APG is based on the same understanding of the mossy fiber–granule cell–

parallel fiber structure as CMAC, using the same state encoder, but has the crucial difference (Fig. 62.2c) that the role of the nuclei is crucial. In the APG model, each nucleus cell is connected to a motor cell in a feedback circuit. Activity in the loop is then modulated by Purkinje cell inhibition, a modeling idea introduced by *Arbib* et al. [62.80].

The learning algorithm determines which of the PF–PC synapses will be updated in order to improve movement generation performance. This is the traditional credit assignment problem: *which* synapse (the structural credit assignment) must be updated based on a response issued *when* (temporal credit assignment). While the former is solved by the CFs, which are considered binary signals, for the latter eligibility traces on the synapses are introduced, serving as memory for recent activity to determine which synapses are eligible for updates. The motivation for the eligibility signal is this: each firing of a PC cell will take some time to affect the animal’s movement, and a further delay will occur before the CF can signal an error in the movement in which the PC is involved. Thus the error signal should not affect those PF–PC synapses which are currently active, but should instead act upon those synapses which affected the activity whose error is now being registered ~~and this the eligibility is timed to signal~~<sup>8</sup>.

The APG has been applied in a few control situations, e.g., a single muscle–mass system and a simulated two-link robot arm. Unfortunately these applications do not allow us judge the performance of the APG scheme itself due to the fact that the control task itself was hidden within spinal cord and muscle models.

#### The Schweighofer–Arbib Model

The Schweighofer–Arbib model was introduced in *Schweighofer* [62.81]. It does not use the CMAC state encoder but tries to copy the anatomy of the cerebellum. All the cells, fibers, and axons in Fig. 62.2a are included. Several assumptions are made: (1) there are two types of mossy fibers, one type reflecting the desired state of the controlled plant and another which carries information on the current state. A mossy fiber diverges into approximately 16 branches; (2) granule cells have an average of four dendrites, each of which receive input from different mossy fibers through a synaptic structure called the glomerulus; (3) three Golgi cells synapse on a granule cell through the glomerulus and the strength of their influence depends on the simulated geometric distance between the glomerulus and the Golgi cell; (4) the climbing fiber connection on nuclear cells as well as deep nuclei is neglected.

Learning in this model depends on directed error information given by the climbing fibers from the inferior olive (IO). Here, long-term depression is performed when the IO firing rate provides an error signal for an eligible synapse, while compensatory but slower increases in synaptic strength can occur when no error signal is present. Schweighofer applied the model to explain several acknowledged cerebellar system functions: (1) saccadic eye movements, (2) two-link limb movement control (see *Schweighofer* et al. [62.82, 83]), and (3) prism adaptation (*Arbib* et al. [62.84]). Furthermore, control of a simulated human arm was demonstrated.

#### Multiple Paired Forward–Inverse Models (MPFIM)

Building on a long history of cerebellar modeling by *Wolpert* and *Kawato* [62.85]<sup>9</sup> proposed a novel functional model of the cerebellum which uses multiple coupled predictors and controllers which are trained for control, each being responsible for a small state-space region. The MPFIM model is based on the indirect/direct model approach by *Kawato*, and is also based on the microcomplex theory. We noted earlier that a microzone is a group of PCs, while a microcomplex combines the PCs of a microzone with their target cells in cerebellar nuclei. In MPFIM, a microzone consists of a set of modules controlling the same degree of freedom and is learned by only one particular climbing fiber. The modules in this microzone compete to control this particular synergy. Inside such a module there are three types of PC which perform the computations of a forward model, an inverse model or a responsibility predictor, but all receiving the same input. A single internal model *i* is considered to be a controller which generates a motor command  $\tau_i$  and a predictor which predicts the current acceleration. Each predictor is a forward model of the controlled system, while each controller contains an inverse model of the system in a region of specialization. The responsibility signal weights the contribution that this model will make to the overall output of the microzone. Indeed, MPFIM further assumes that each microzone contains *n* internal models of situations occurring in the control task. Model *i* generates motor command  $\tau_i$ , and estimates its own responsibility  $r_i$ . The feedforward motor command  $\tau_{ff}$  consists only of the output of the single models adjusted by the sum of responsibility signals:  $\tau_{ff} = \sum r_i \tau_i / \sum r_i$ .

The PCs are considered to be roughly linear. The MF inputs carry all necessary information including state information, efference copies of the last motor commands as well as desired states. Granule cells, and eventually

<sup>8</sup> Please check this sentence  
<sup>9</sup> Please check this sentence

the inhibitory interneurons as well, nonlinearly transform the state information to provide a rich set of basis functions through the PFs. A climbing fiber carries a scalar error signal while each Purkinje cell encodes a scalar output – responsibilities, predictions, and controller outputs are all one-dimensional values. MPFIM has been introduced with different learning methods: its first implementations were done using gradient descent methods; subsequently, expectation maximization (EM) batch-learning and hidden Markov chain EM learning have been applied.

#### Comparison of the Models

Summing up, we can categorize the cerebellar models CMAC, APG, Schweighofer–Arbib, and MPFIM as follows.

- State-encoder-driven models: This kind of model assumes that the granule cells are on-off types of entities which split up the state space. This kind of model is best suited for, e.g., simple function approximation, and suffers strongly from the curse of dimensionality.
- Cellular-level models: Obviously, the most realistic simulations would be at the cellular level. Unfortunately, modeling only a few Purkinje cells at realistic conditions is an immense computational challenge, and other relevant neurons are even less well understood. Still, from the biological point of view this kind of model is the most important since it allows obtaining insight into cerebellar function on cellular level. The first steps in this direction were taken by the Schweighofer–Arbib model.
- Functional models: From the computer-science point of view, the most interesting models are based on functional understanding of the cells. In this case, we obtain only a basic insight of the functions of the parts and apply it as a crude approximation. This kind of approach is very promising and MPFIM, with its emphasis on the use of responsibility signals to combine models appropriately, provides an interesting example of this approach.

### 62.3.3 Cerebellar Models and Robotics

From the previous discussions, it is clear that a popular view is that the function of the cerebellum within the motor control loop is to represent a forward model of the skeletomuscular system. As such it predicts the movements of the body, or rather the perceptually coded (e.g., through muscle spindles, skin-based positional in-

formation, and visual feedback) representation of the movements of the body. With this prediction a fast control loop between motor cortex and cerebellum can be realized, and motor programs are played before being sent to the spinal cord (Fig. 62.4). Proprioceptive feedback is used for adaptation of the motor programs as well as for updating the forward model stored in the cerebellum. However, the Schweighofer–Arbib model is based on the view that the cerebellum offers not so much a total forward model of the skeletomuscular system as a forward model of the *difference* between the crude model of the skeletomuscular system available to the motor planning circuits of the cerebral cortex, and the more intricately parameterized forward model of the skeletomuscular system needed to support fast, graceful movements with minimal use of feedback. This hypothesis is reinforced by the fact that cerebellar lesions do not prohibit motion but substantially reduce its quality, since the forward model of the skeletomuscular system is of lesser quality.

As robotic systems move towards their biological counterparts, the control approaches can or must do the same. There are many lines of research investigating the former part; cf. Chap. 013<sup>CE10</sup> *Flexible Arms* and Chap. 060<sup>CE10</sup> *Biologically Inspired Robots*. It should be noted that the drive principle that is used to move the joints does not necessarily have a major impact on the outer control loop. Whether McKibben muscles, which are intrinsically flexible but bulky (see *van der Smagt* et al. [62.86]), low-dynamics polymer linear actuators, or direct-current (DC) motors with spindles and added elastic components are used does not affect the control approach at the cerebellar level, but rather at the motor control level (cf. the spinal cord level). Of key importance, however, are the resulting dynamical properties of the system, which are of course influenced by its actuators.

Passive flexibility at the joints, which is a key feature of muscle systems, is essential for reasons of safety, stability during contact with the environment, and storage of kinetic energy. As mentioned before, however, biological systems are immensely complex, requiring large groups of muscles for comparatively simple movements. A reason for this complexity is the resulting nearly linear behavior, which has been noted for, e.g., muscle activation with respect to joint stiffness (see *Osu and Gomi* [62.87]). By this regularization of the complexity of the skeletomuscular system, the complexity of the forward model stored in the cerebellum is correspondingly reduced. The whole picture therefore seems to be that the cere-

<sup>CE10</sup> Please check this internal reference

bellum, controlling a piecewise-linear skeletomuscular system, incorporates a forward model thereof to cope with delays in the peripheral nervous system. Consequently, although the applicability of cerebellar systems to highly nonlinear dynamics control of traditional robots is questionable, the use of cerebellar systems as

forward models appears to be useful in the control of more complex and flexible robotic systems. The control challenge posed by the currently emerging generation of robots employing antagonistic motor control therefore opens a new wealth of applications of cerebellar systems.

## 62.4 The Role of Mirror Systems

*Mirror neurons* were first discovered in the brain of the macaque monkey – neurons that fire both when the monkey exhibits a particular grasping action, and when the monkey observes another (monkey or human) perform a similar grasp (see *Rizzolatti et al.* [62.88] and *Gallese et al.* [62.89]). Since then, human studies have revealed a *mirror system* for grasping in the human brain – a mirror system for a class X of actions being a set of regions that are active both when the human performs some action from X and when the human observes someone else performing an action from X (see, e.g., *Grafton et al.* [62.90], *Rizzolatti et al.* [62.91], and *Fadiga et al.* [62.92]). Until recently we had no single-neuron studies of humans proving the reasonable hypothesis that the human mirror system for grasping contains *mirror neurons* for specific actions. However, data from neurosurgery are now becoming available (M. Iacoboni, personal communication). In any case, most models of the human mirror system for grasping assume that it contains circuitry analogous to the mirror neuron circuitry of the macaque brain. However, the current consensus is that monkeys have little or no ability for imitation (but see *Voelkl and Huber* [62.93] for a very simple form of imitation-like behavior in marmoset monkeys); great apes have the ability to master certain skills after extended bouts of observation (*Byrne* [62.94]), whereas the human mirror system plays a key role in our capability for much richer forms of imitation (see *Iacoboni et al.* [62.95]), pantomime, and even language (see *Arbib and Rizzolatti* [62.96] and *Arbib* [62.97]). Indeed, it has been suggested that mirror neurons underlie the motor theory of speech perception of *Lieberman et al.* [62.98], which holds that speech perception rests on the ability to recognize the motor acts that produce speech sounds.

Section 62.4.1 reviews basic neurophysiological data on mirror neurons in the macaque, and presents both the Fagg–Arbib–Rizzolatti–Sakata (FARS) model of canonical neurons (unlike mirror neurons, these are active when the monkey executes an action but not when

he observes it) and the mirror neuron system (MNS) model of mirror neurons and their supporting brain regions. Section 62.4.2 then uses Bayes's rule to offer a new, probabilistic view of the mirror system's role in action recognition, and demonstrates the operation of the new model in the context of studies with two robots. Finally, Sect. 62.4.3 briefly shifts the emphasis of our study of mirror neurons to imitation, which in fact is the area that has most captured the imagination of roboticists.

### 62.4.1 Mirror Neurons and the Recognition of Hand Movements

Area F5 in the premotor cortex of the macaque contains, among others, neurons which fire when the monkey executes a specific manual action, e.g., one neuron might fire when the monkey performs a precision pinch, another when it executes a power grasp. (In discussing neurorobotics, it seems unnecessary to explain in any detail the areas like F5, AIP, and STS described here – they will function as labels for components of functional systems. To fill in the missing details see, e.g., *Rizzolatti et al.* [62.99, 100]) A subset of these neurons, the so-called *mirror neurons*, also discharge when the monkey observes meaningful hand movements made by the experimenter which are similar to those whose execution is associated with the firing of the neuron. In contrast, the *canonical neurons* are those belonging to the complementary, anatomically segregated subset of grasp-related F5 neurons which fire when the monkey performs a specific action and also when it sees an object as a possible target of such an action – but do not fire when the monkey sees another monkey or human perform the action. Finally, F5 contains a large population of motor neurons which are active when the monkey grasps an object (either with the hand or mouth) but do not possess any visual response. F5 is clearly a motor area although the details of the muscular activation are abstracted out – F5 neurons can be effector-independent. In contrast, the primary motor cortex (F1) formulates

the neural instructions for lower motor areas and motor neurons.

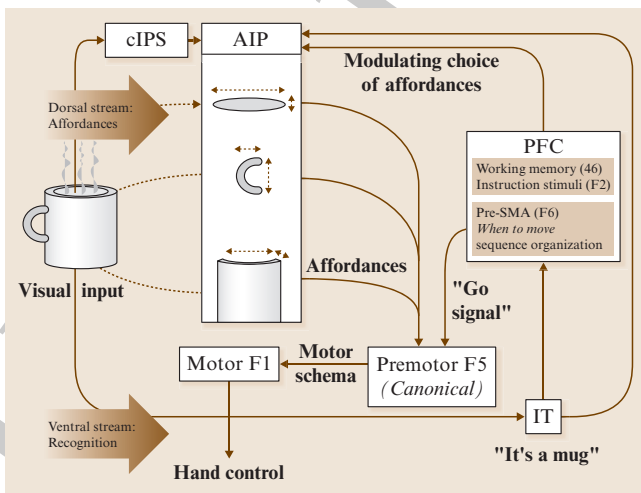
Moreover, macaque mirror neurons encode transitive actions and do not fire when the monkey sees the hand movement unless it can also see the object or, more subtly, if the object is not visible but is appropriately *located* in working memory because it has recently been placed on a surface and has then been obscured behind a screen behind which the experimenter is seen to be reaching (see *Umiltà* et al. [62.101]). All mirror neurons show visual generalization. They fire when the instrument of the observed action (usually a hand) is large or small, far from or close to the monkey. They may also fire even when the action instrument has shapes as different as those of a human or monkey hand. Some neurons respond even when the object is grasped by the mouth. When naive monkeys first see small objects grasped with a pair of pliers, mirror neurons do not respond, but after extensive training some precision pinch mirror neurons do show activity also to this new grasp type (see *Ferrari* et al. [62.102]).

Mirror neurons for grasping have also been found in parietal areas of the macaque brain and, recently, it has been shown that parietal mirror neurons are sensitive to the context of the observed action being predictive of the outcome as a function of contextual cues – e.g., some grasp-related parietal mirror neurons may fire for a grasp that precedes eating the grasped object while

others fire for a grasp that precedes placing the object in a container (see *Fogassi* et al. [62.103]). In practice the parieto-frontal circuitry seems to encode action execution and simultaneously action recognition by taking into account a large set of potential candidate actions which are selected on the basis of a range of cues such as vision of the relation of the effector to the object and certain sounds (when relevant for the task). Further, feedback connections (frontal to parietal) are thought to be part of a stimulus selection process which refines the sensory processing by *attending* to stimuli relevant for the ongoing action (see *Rizzolatti* et al. [62.58] and recall the discussion in Sect. 62.2.5). Recognition is then supported by the activation of the same circuitry in the absence of overt movement.

We clarify these ideas by briefly presenting the FARS model of the canonical F5 neurons and the MNS model of the F5 mirror neurons. In each case, the F5 neurons function effectively only because of the interaction of F5 with a wide range of other regions. We have stressed (Sect. 62.2.3) the distinction between recognition of the category of an object and recognition of its *affordances*. The parietal area AIP processes visual information to extract *affordances*, in this case properties of the object relevant to grasping it (*Taira* et al. [62.104]). AIP and F5 are reciprocally connected, with AIP being more visual and F5 more motoric.

The Fagg–Arbib–Rizzolatti–Sakata (FARS) model (see *Fagg* and *Arbib* [62.105] and Fig. 62.6) embeds F5 canonical neurons in a larger system. The dorsal stream (which passes through AIP) can only analyze the object as a set of possible affordances, whereas the ventral stream (via the inferotemporal cortex, IT) is able to recognize what the object is. The latter information is passed to the prefrontal cortex (PFC) which can then, on the basis of the current goals of the organism, bias the choice of affordances appropriate to the task at hand. Neuroanatomical data (as analyzed by *Rizzolatti* and *Luppino* [62.106]) suggest that PFC and IT may modulate action selection at the level of the parietal cortex. Figure 62.6 gives a partial view of the FARS model updated to show this modified pathway. The affordance selected by AIP activates F5 neurons to command the appropriate grip once they receive a *go* signal from another region, F6, of the prefrontal cortex. F5 also accepts signals from other PFC areas to respond to working memory and instruction stimuli in choosing among the available affordances. Note that this same pathway could be implicated in tool use, bringing in semantic knowledge as well as perceptual attributes to guide the dorsal system (see *Johnson–Frey* [62.107]).



**Fig. 62.6** The original FARS diagram (see *Fagg* and *Arbib* [62.41]) is here modified to show PFC acting on AIP rather than F5. The idea is that the prefrontal cortex uses the IT identification of the object, in concert with task analysis and working memory, to help the AIP select the appropriate affordance from its *menu*

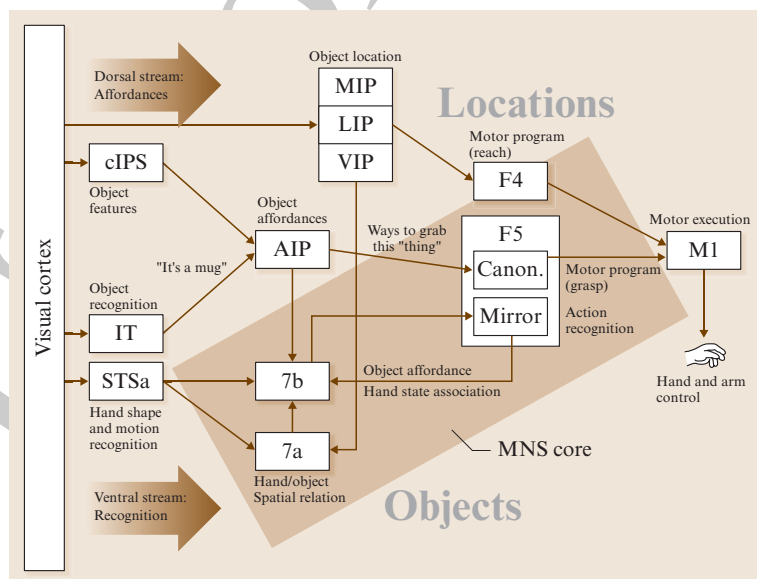


With this, we turn to the *mirror* system. Since grasping a complex object requires careful attention to motion of, e.g., fingertips relative to the object we hold that the primary evolutionary impetus for the mirror system was to facilitate feedback control of dexterous movement. We now show how *parameters relevant to such feedback* could be crucial in enabling the monkey to associate the visual appearance of what it is doing with the task at hand. The key side-effect will be that this feedback-serving self-recognition is so structured as to also support recognition of the action when performed by others – and it is this *recognition of the actions of others* that has created the greatest interest in mirror neurons and systems.

The MNS model of *Oztop* and *Arbib* [62.108] provides some insight into the anatomy while focusing on the learning capacities of mirror neurons. Here, the task is to determine whether the shape of the hand and its trajectory are *on track* to grasp an observed affordance of an object using a known action. The model is organized around the idea that the AIP → F5<sub>canonical</sub> pathway emphasized in the FARS model (Fig. 62.6) is complemented by another pathway 7b → F5<sub>mirror</sub>. As shown in Fig. 62.7 (middle diagonal), object features are processed by AIP to extract grasp affordances, these are sent on to the canonical neurons of F5 that choose a particular grasp. Recognizing the location of the object (top diagonal) provides parameters to the motor programming area F4 which computes the reach. The information about the reach and the grasp is taken by the motor cortex

M1 (=F1) to control the hand and the arm. The rest of the figure provides components that can learn and apply key criteria for activating a mirror neuron, recognizing that the preshape of the observed hand corresponds to the grasp that the mirror neuron encodes and is appropriate to the object, and that the hand is moving on an appropriate trajectory. Making crucial use of input from the superior temporal sulcus (STSa; see *Perrett et al.* [62.109] and *Carey et al.* (1997)<sup>TS3</sup>), schemas at the bottom left recognize the shape of the observed hand, and how that hand is moving. Other schemas implement hand–object spatial relation analysis and check how object affordances relate to hand state. Together with F5 canonical neurons, this last schema (in parietal area 7b) provides the input to the F5 mirror neurons.

In the MNS model, the *hand state* was defined as a vector whose components represented the movement of the wrist relative to the location of the object and of the hand shape relative to the affordances of the object. *Oztop* and *Arbib* showed that an artificial neural network corresponding to PF and F5<sub>mirror</sub> could be trained to recognize the grasp type from the *hand state trajectory*, with correct classification often being achieved well before the hand reached the object, using activity in the F5 canonical neurons that commands a grasp as training signal for recognizing it visually. Crucially, this training prepares the F5 mirror neurons to respond to hand–object relational trajectories even when the hand is of the *other* rather than the *self* because the hand state is based on the view of movement of a hand relative to



**Fig. 62.7** The mirror neuron system (MNS) model (see *Oztop* and *Arbib* [62.88]). Note that this basic mirror system for grasping crucially links the visual process of the superior temporal sulcus (STS) to the parietal regions (b) and premotor regions (F5) which have been shown to contain mirror neurons for manual actions

the object, and thus only *indirectly* on the retinal input of seeing hand and object, which can differ greatly between observation of self and other. Bonaiuto et al. [62.110] have developed MNS2, a new version of the MNS model to address data on audiovisual mirror neurons that respond to the sight and sound of actions with characteristic sounds such as paper tearing and nut cracking (see Kohler et al. [62.101]), and on the response of mirror neurons when the target object was recently visible but is currently hidden (see Umiltá et al. [62.101]). Such learning models, and the data they address, make clear that *mirror neurons are not restricted to recognition of an innate set of actions but can be recruited to recognize and encode an expanding repertoire of novel actions.*

The discussion of this section avoided any reference to imitation (Sect. 62.4.3). On the other hand, even without considering imitation, mirror neurons provide a new perspective for tackling the problem of robotic perception by incorporating action (and motor information) into a plausible recognition process. The role of the fronto-parietal system in relating affordances, plans, and actions shows the crucial role of motor information and embodiment. We argue that this holds lessons for neurorobotics: the richness of the *motor* system should strongly influence what the robot can learn, proceeding autonomously via a process of exploration of the environment rather than overly relying on the intermediary of logic-like formalisms. When recognition exploits the ability to act, then the breadth of the action space becomes crucially related to the precision, quality, and robustness of the robot's perception.

#### 62.4.2 A Bayesian View of the Mirror System

We now show how to cast much that is known about the mirror system into a controller–predictor model (see Miall et al. [62.50] and Wolpert et al. [62.111]) and analyze the system in Bayesian terms. As shown by the FARS model, the decision to initiate a particular grasping action is attained by the convergence in area F5 of several factors including contextual and object-related information; similarly many factors affect the recognition of an action. All this depends on learning both *direct* (from decision to executed action) and *inverse* models (from observation of an action to activation of a motor command that could yield it). Similar procedures are well known in the computational motor control literature (see Jordan and Rumelhart [62.112] and Kawato et al. [62.113]). Learning of the affordances of objects with respect to grasping can also be achieved

autonomously by learning from the consequences of applying many different actions to different parts of different objects.

But how is the decision made to classify an observed behavior as an instance of one action or another? Many comparisons could be performed in parallel with the model for one action becoming predominantly activated. There are plausible implementations of this mechanism using a gating network (see Demiris and Johnson [62.114] and Haruno et al. [62.115]). A gating network learns to partition an input space into regions; for each region a different model can be applied or a set of models can be combined through an appropriate weight function. The design of the gating network can encourage collaboration between models (e.g., linear combination of models) or competition (choosing only one model rather than a combination). Oztop et al. [62.116] offer a similar approach to the estimation of the mental states of the observed actor, using some additional circuitry involving the frontal cortex.

We now offer a Bayesian view of using the predictor–controller formulation approach to the mirror system. This Bayesian approach views affordances as priors in the action recognition process where the evidence is conveyed by the visual information of the hand, providing the data for finding the posterior probabilities as mirror neurons-like responses which automatically activate for the most probable observed action. Recalling that the presence of a goal (at least in working memory) is needed to elicit mirror neuron responses in the macaque. We believe it is also particularly important during the ontogenesis of the human mirror system, for example, Woodward [62.117] has shown that even at nine months of age, infants recognized an action as being novel if it was directed toward a novel object rather than just having different kinematics, showing that the goal is more fundamental than the enacted trajectory. Similarly, if one sees someone drinking from a coffee mug then one can hypothesize that a particular action (that one already knows in motor terms) is used to obtain that particular effect. The association between the canonical response (object–action) and the mirror one (including vision) is made when the observed consequences (or goal) are recognized as similar in the two cases. Similarity can be evaluated following criteria ranging from kinematic to social consequences.

Many formulations of recognition tasks are available in the literature (see Duda, Hart, and Stork [62.118]) besides those keyed to the study of mirror neurons. Here, however, we focus on the Metta et al. [62.119] Bayesian interpretation of the recognition of actions.

We equate the prior probabilities for actions with the object affordances, that is:

$$p(A_i|O_k), \tag{62.1}$$

where  $A_i$  is the  $i$ -th action from a motor repertoire of  $I$  actions and  $O_k$  is the target object of the grasping action out of a set of  $K$  possible objects. The affordances of an object identify the set of actions that are most likely to be executed upon it, and consequently the mirror activation of F5 can be thought as:

$$p(A_i|F, O_k), \tag{62.2}$$

where  $F$  are the features obtained by observation of the trajectory of the temporal evolution of the observed action. This probability can be computed from Bayes rule as

$$p(A_i|F, O_k) = p(F|A_i, O_k)p(A_i|O_k). \tag{62.3}$$

(An irrelevant normalization factor has been neglected so that, strictly speaking, the posterior in (62.3) is no longer a probability.) With this, a classifier is constructed by taking the maximum over the possible actions

$$\hat{A} = \max_i p(A_i|F, O_k). \tag{62.4}$$

Following Lopes and Santos-Victor [62.120], Metta et al. <sup>TS5</sup> assumed that the features  $F$  along the trajectories are independent. This is clearly not true for a smooth trajectory linking the movement of the hand and fingers to the observed action. However, this approximation simplified the estimation of the likelihoods in equation, though later implementations should take into account the dependence across time.

The object recognition stage (i. e., finding  $O_k$ ) requires as much vision as is needed to determine the probability of the various grasp types being effective, the hand features  $F$  correspond to the STS response, and the response of the mirror neurons determines the most probable observed action  $A_i$ . We can identify certain circuits in the brain with the quantities described before.

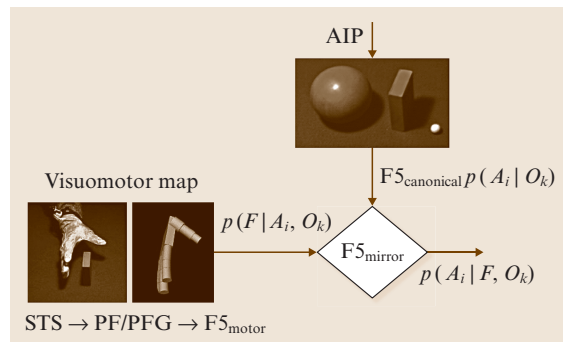
However Table 62.1 does not exhaust the various computations required in the model. In the *learning phase*, the visuomotor map is learned by a sigmoidal feedforward neural network trained with the backpropagation algorithm (both visual and motor signals are available); affordances are learned simply by counting the number of occurrences of actions given the object (visual processing of object features was assumed); and the likelihood was approximated by a mixture of Gaussians and the parameters learned by the expectation

**Table 62.1** Brain quantities and circuits

$p(A_i F, O_k)$	Mirror neuron responses, obtained by a combination of the information as in (62.3)
$p(F A_i, O_k)$	The activity of the F5 motor neurons generating certain motor patterns given the selected action and the target object
$p(A_i O_k)$	Object affordances: the response of the circuit linking AIP and the F5 canonical neurons AIP→F5
Visuomotor map	Transformation of the hand-related visual information into motor data: identified with the response of STS → PF/PFG → F5, which is represented in F5 by $p(F A_i, O_k)$

maximization (EM) algorithm. During the *recognition phase*, motor information is not available, but is recovered from the visuomotor map. Figure 62.8 shows a block diagram of the operation of the classifier.

A comparison (see Lopes and Santos-Victor [62.120]) was made of system performance: (a) when using the output of the inverse model and thus employing motor features to aid classification during the training phase, and (b) when only visual data were available for classification. Overall, their interpretation of the results is that by mapping in motor space they allow the classifier to choose features that are much better suited for



**Fig. 62.8** Block diagram of the recognition process. Recognition (mirror neuron activation) is due to the convergence in F5 of two main contributions: signals from the AIP-F5 canonical connections and signals from the STS-PF/PFG-F5 circuit. In this model, activations are thought of as probabilities and are combined using Bayes's rule

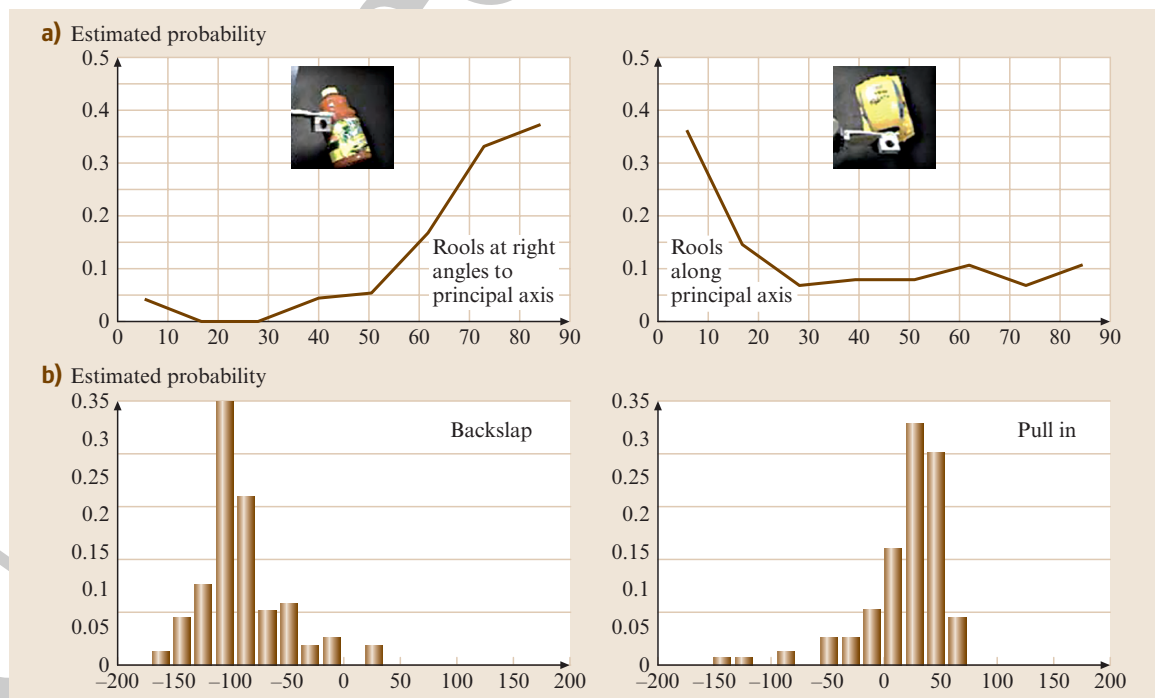
performing optimally, which in turn facilitates generalization. The same is not true in visual space, since a given action may be viewed from different viewpoints. One may compare this to the viewpoint invariance of hand state adopted in the MNS model, which has the weakness there of being built in rather than emerging from training.

Another set of experiments was performed on a humanoid robot upper torso called Cog (see Brooks et al. [62.28]). Cog has a head, arms, and a moving waist for a total of 22 degrees of freedom but does not have hands. It has instead simple flippers that could be used to push and prod objects. Fitzpatrick and Metta [62.121] and Metta et al. [62.119] were interested in starting from minimal initial hypotheses yet yielding units with responses similar to mirror neurons. The robot was programmed to identify suitable cues to start the interaction with the environment and direct its attention towards potential objects, using an attention system similar to that (see Itti and Koch [62.52]) described in Sect. 62.2.5. Although the robot could not

grasp objects, it could generate useful cues from touch, push, and prod actions.

The problem of defining objects reflects the problem of segmenting the visual scene. Criteria such as contrast, binocular disparity, and motion can be applied, but any of them can fail in a given situation. In the present system, optic flow was used to detect and segment an object after impact with the arm end point, and from segmentation based on shape, color, and behavior data. Depending on the available motor repertoire, the robot could explore a range of possible object behaviors (affordances) and form an object model which combines both sensorial and motor properties of the object the robot had the chance to interact with.

In a typical experiment, the human operator waves an object in front of the robot, which reacts by looking at it. If the object is dropped on the table in front of the robot, a reaching action is initiated, and the robot possibly makes contact with the object. Vision is used during the reaching and touching movement to guide the robot's flipper toward the object, to segment the hand from the



**Fig. 62.9** (a) The affordances of two objects: a toy car and a bottle represented as the probability of moving along a given direction measured with respect to the object principal axis (visual). It is evident that the toy car tends to move mostly along the direction identified with the principal axis and the orange juice bottle at a right angle with respect to its principal axis. (b) The probability of a given action generating a certain object movement. The reference frame is anchored to the image plane in this case

object upon contact, and to collect information about the behavior of the object caused by the application of a certain action (see *Fitzpatrick* [62.122]). Unfortunately, interaction of the robot's flipper with objects does not result in a wide class of different affordances and so this study focused on the rolling affordances of a toy car, an orange juice bottle, a ball, and a colored toy cube. Besides reaching, the robot's motor repertoire consists of four different stereotyped approach movements covering a range of directions of about  $180^\circ$  around the object. For each successful trial, the robot stored the result of the segmentation, the object's principal axis which was selected as representative shape parameter, the action – initially selected randomly from the set of four approach directions – and the movement of the center of mass of the object for some hundreds of milliseconds after impact with the flipper was detected. This gives information about the rolling properties (affordances) of the different objects, e.g., the car tends to roll along its principal axis, the bottle at a right angle with respect to the axis. Figure 62.9 shows the result of collecting about 700 samples of generic poking actions and estimating the average direction of displacement of the object. Note, for example, that the action labeled as *backslap* (moving the object with the flipper outward from the robot) consistently gives a visual object motion upward in the image plane (corresponding to the peak at  $-100^\circ$ ,  $0^\circ$  being the direction parallel to the image  $x$ -axis; the  $y$ -axis pointing downward). A similar consideration applies to the other actions. Although crude, this implementation shows that with little pre-existing structure the robot could acquire the crucial elements for building knowledge of objects in terms of their affordances. Given a sufficient level of abstraction, this implementation is close to the response of canonical neurons in F5 and their interaction with neurons observed in AIP that respond to object orientation (see *Sakata et al.* [62.123]).

### 62.4.3 Mirror Neurons and Imitation

*Fitzpatrick and Metta* [62.121] also addressed the question of what is further required for interpreting observed actions. Where in the previous section, the robot identified the motion of the object because of a specific action applied to it, here it could backtrack and derive the type of action from the observed motion of the object. It can further explore what is causing motion and learn about the concept of manipulator in a more general setting. In fact, the same segmentation procedure mentioned earlier could visually interpret poking actions generated by a human as well as those generated by the robot.

One might argue that observation could be exploited for learning about object affordances. This is possibly true to the extent passive vision is reliable and action is not required. The advantage of the active approach, at least for the robot, is that it allows controlling the amount of information impinging on the visual sensors by, for instance, controlling the speed and type of action. This strategy might be especially useful given the limitations of artificial perceptual systems. Thus, observations can be converted into interpreted actions. The action whose effects are closest to the observed consequences on the object (which we might translate into the goal of the action) is selected as the most plausible interpretation given the observation. Most importantly, the interpretation reduces to the interpretation of the *simple* kinematics of the goal and consequences of the action rather than to understanding the *complex* kinematics of the human manipulator. The robot understands only to the extent it has learned to act. One might note that a more refined model should probably include visual cues from the appearance of the manipulator into the interpretation process. Indeed, the *hand state* that was central to the *Oztop–Arbib* model was based on an object-centered view of the hand's trajectory in a coordinate frame based on the object's affordances. The last question to address is whether the robot can imitate the *goal* of a poking action. The step is indeed small since most of the work is actually in interpreting observations. Imitation was generated in the following by replicating the latest observed human movement with respect to the object and irrespective of its orientation, for example, in case the experimenter poked the toy car sideways, the robot imitated him/her by pushing the car sideways. Starting from this simple experiment, we need to formalize what is required for a system that has to acquire and deliver imitation.

Roboticians have been fascinated by the discovery of mirror neurons and the purported link to imitation that exists in the human nervous system. The literature on the topic extends from models of the monkey's (nonimitative) action recognition system (see *Oztop* and *Arbib* [62.108]) to models of the putative role of the mirror system in imitation (see *Demiris* and *Johnson* [62.114] and *Arbib et al.* [62.124]), and in real and virtual robots (see *Schaal et al.* [62.125]). *Oztop et al.* [62.126] propose a taxonomy of the models of the mirror system for recognition and imitation, and it is interesting to note how different the computational approaches that have been now framed as mirror system models are, including recurrent neural networks with parametric bias (see *Tani et al.* [62.127]),

behavior-based modular networks (see *Demiris* and *Johnson* [62.114]), associative memory-based methods (see *Kuniyoshi* et al. [62.128]), and the use of multiple direct-inverse models as in the MOSAIC architecture (*Wolpert* et al. [62.129]; cf. the multiple paired forward-inverse models of Sect. 62.3.2).

Following the work of *Schaal* et al. [62.125] and *Oztop* et al. [62.126] we can propose a set of schemas required to produce imitation:

- determine what to imitate, inferring the goal of the demonstrator,
- establish a metric for imitation (correspondence; see *Nehaniv* [62.130]),
- map between dissimilar bodies (mapping),
- imitate behavior formation,

which are also discussed in greater detail by *Nehaniv* and *Dautenhahn* [62.131]. In practice, computational and robotic implementations have tackled these problems with different approaches and emphasizing different parts or specific subproblems of the whole, for example, in the work of *Demiris* and *Hayes* [62.132], the rehearsal of the various actions (akin to the aforementioned theory of motor perception) was used to generate hypotheses to be compared with the actual sensory input. It is then remarkable how more recently a modified approach of this paradigm has been used in comparison with real human transcranial magnetic stimulation (TMS) data.

*Ito* et al. [62.133] (not the Masao Ito of cerebellar fame) took a dynamical systems approach using a recurrent neural network with parametric bias (RNNPB)

to teach a humanoid robot to manipulate certain objects. In this approach the parametric bias (PB) encodes (tags) certain sensorimotor trajectories. Once learning is complete the neural network can be used either to recall a given trajectory by setting the PB externally or provide input for the sensory data only and observe the PB vector that would represent in that case the recognition of the situation on the basis of the sensory input only (no motor information available). It is relatively easy to interpret these two situations as the motor generation and the observation in a mirror neurons model.

The problem of building useful mappings between dissimilar bodies (consider a human imitating a bird's flapping wings) was tackled by *Nehaniv* and *Dautenhahn* [62.131] where an algebraic framework for imitation is described and the correspondence problem formally addressed. Any system implementing imitation should clearly provide a mapping between either dissimilar bodies or even in the case of similar bodies when either the kinematics or dynamics is different depending on the context of the imitative action.

*Sausser* and *Billard* [62.134] modeled the *ideomotor principle*, according to which observing the behavior of others influences our own performances. The ideomotor principle points directly to one of the core issues of the mirror system, that is, the fact that watching somebody else's actions changes something in the activation of the observer, thus facilitating certain neural pathways. The work in question also gives a model implemented in terms of neural fields (see *Sausser* and *Billard* [62.134] for details) and tries to explain the imitative cortical pathways and the behavior formation.

## 62.5 Extrodution

As the foregoing makes clear, robotics has much to learn from neuroscience and much to teach neuroscience. Neurorobotics can learn from the ways in which the brains and bodies of different creatures adapt to diverse ecological niches – as computational neuroethology helps us understand how the brain of a creature has evolved to serve *action-oriented perception*, and the attendant processes of learning, memory, planning, and social interaction.

We have sampled the *design* of just a few subsystems (both functional and structural) in just a few animals – optic flow in the bee, approach, escape, and barrier avoidance in frogs and toads, and navigation in the rat, as well as the control of eye movements in visual atten-

tion, the role of mammalian cerebellum in handling the nonlinearities and time delays of flexible motor systems, and the mirror systems of primates in action recognition and of humans in imitation. There are many more creatures with lessons to offer the roboticist than we can sample here.

Moreover, if we just confine attention to the brains of humans, this Chapter has mentioned at least 7a, 7b, AIP, area 46, caudo-putamen, cerebellum, cIPS, F2, F4, F5, hippocampus, hypothalamus, inferotemporal cortex, LIP, MIP, motor cortex, nucleus accumbens, parietal cortex, prefrontal cortex, premotor cortex, pre-SMA (F6), spinal cord, STS, and VIP – and it is clear that there are many more details to be understood for

each region, and many more regions whose interactions hold lessons for roboticists. We say this not to depress the reader, but rather to encourage further exploration of the literature of computational neuroscience and to note that the exchange with neurorobotics proceeds both ways: neuroscience can inspire novel robotic

designs; conversely, robots can be used to test whether brain models still work when they make the transition from disembodied computer simulation to meeting the challenge of guiding the interactions of a physically embodied system with the complexities of its environment.

## 62.6 Further Reading

M.A. Arbib, (Ed.): *From Action to Language via the Mirror System* (Cambridge Univ. Press, Cambridge 2006).

This volume provides 16 articles on the mirror system, written by diverse experts. Of particular relevance to this Chapter are articles on dynamical systems: brain, body and imitation; attention and the minimal subscene; the development of grasping and the mirror system; and development of goal-directed imitation, object manipulation and language in humans and robots.

C. Bell, P. Cordo, S. Harnad: Controversies in neuroscience IV: motor learning and plasticity in the cerebellum. *Behavioral and brain sciences* **19**(3), (1996)

This somewhat older BBS special issue lists a back<sup>CE 11</sup> then rather definitive number of articles on the cerebellum, including an overview of models in a paper by Houk et al.

P. van der Smagt, D. Bullock: Applied intelligence, Scalable Applications of Neural Networks to Robotics **17**(1), (2002).

This special issue is focused on the application of cerebellar and other models to robotics tasks, and

lists some successful and – between the lines – more unsuccessful applications thereof.

V. Gallese, L. Fadiga, L. Fogassi, G. Rizzolatti: Action recognition in the premotor cortex. *Brain* **119**, 593–609 (1996)

This paper provides a detailed account of the neurophysiological evidence for mirror neurons. It is good reading to get the real data unbiased from further interpretation on the role of mirror neurons and it is complete and accurate. Although it is a technical paper it is easy to read also to a general audience.

L. Fadiga, L. Craighero, G. Buccino, G. Rizzolatti: Speech listening specifically modulates the excitability of tongue muscles: a TMS study. *Eur. J. Neurosci.* **15**(2), 399–402 (2002)

This work extends the mirror concept to language: another interesting extension and perspective on the role of the mirror system into language. This paper is interesting reading by providing evidence in humans (the other references above are about monkey experiments). In this case, it has been shown that speech listening facilitates the activation of tongue muscles which match the specific phoneme being listened to.

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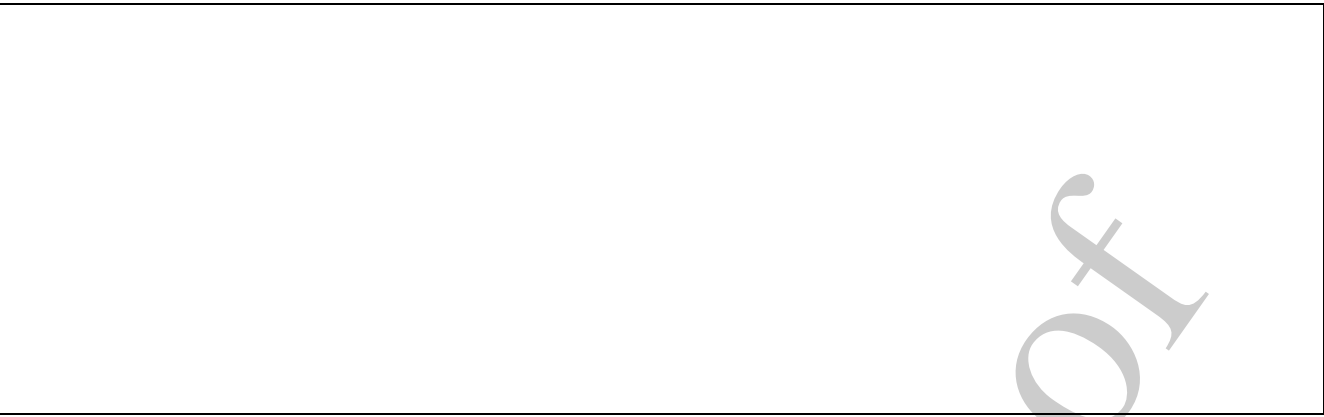


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Uncorrected Proof