

## Chapter 3

# For Further Study

To deepen your knowledge of hierarchical intelligent control, its connections to cognitive neuroscience, and complex applications (e.g., vehicular or robotic) where the methods of this part are used, see [11, 78]. For more discussion on autonomy, see [22] and for a philosophical discussion on the advantages and disadvantages of biomimicry, physics, and mathematics in control and automation system development see [407]. To gain a better understanding of cognitive neuroscience, a good place to start is to read [421] and then to deepen your knowledge, read [206, 268]. There are many good books on general psychology (see, e.g., [223]) and you may want to pursue several of the topics you find there in more detail (e.g., in learning theory). To deepen your understanding of evolution, you could start with [537] and then read [185].

**Conventional Control:** The more that you understand about conventional control, the more you will be able to appreciate some of the finer details of the operation of intelligent control systems. We realize that all readers may not be familiar with all areas of control, so next we provide a list of books from which the major topics can be learned. There are many good texts on classical control [183, 292, 184, 153, 131, 29]. State-space methods and optimal and multivariable control can be studied in several of these texts and also in [187, 100, 15, 32, 341]. Robust control is treated in [398, 154, 557]. Control of infinite dimensional systems is covered in [181, 111]. Nonlinear control is covered in [277, 526, 33, 470, 518, 519, 257, 289]; stability analysis in [360, 357]; and adaptive control in [254, 289, 448, 30, 219, 376]. System identification is treated in [331] (and in the adaptive control texts), and optimal estimation and stochastic control are covered in [291, 315, 314, 228]. A relatively complete treatment of the field of control is in [311] and there are many further references there.

**Hierarchical Intelligent Control:** For a general introduction to the issues in hierarchical intelligent and autonomous control, see the books [21, 234, 520,

536, 517, 11] or articles [22, 20, 10, 489, 77, 78]. The general areas in conventional control of “large scale systems” (or “interconnected” or “decentralized” systems) [357] and game theory [47] are particularly relevant to the study of hierarchical intelligent control. There has probably been more applications-directed research activity in the use of hierarchical distributed controllers, and intelligent autonomous control, in the area of robotic systems (and “swarm robotics”) [76, 77, 78, 44, 258, 23, 520, 144, 156, 73, 11, 483, 135] than any other application area. Connected to this research are studies on intelligent manufacturing systems [294, 11]. For an introduction to control system problems in intelligent vehicle and highway systems, see [177].

Planning systems are also discussed in [444, 387, 136, 11] (a nice discussion on hierarchical and adaptive planning is in [136]) and in [137]. Agents are discussed in [444, 535] and elsewhere. For some examples of distributed multiagent systems, see [409] where the FMS and computer network load balancing problems discussed in the section on multiagent systems are discussed in more detail. Another example of a distributed multiagent system is given in [17], where the authors study distributed adaptive fuzzy control for an FMS.

For more details on design and software implementation of complex hierarchical and distributed control systems, see [197] or the introductory article [365] (where other software packages are also discussed). A relevant study of software for real-time control (the “open control platform”) is in [446].

**Computer Science and Engineering:** There are many subfields in electrical engineering and computer science that contribute to aspects of computer software and hardware development, concepts, and methodology that are relevant to the development of control systems. For instance, the area of computer languages, structured programming, and processor technologies has a significant impact. The emerging area of software architectures [465] can have an impact on how we structure large complex control system software. The important area of software engineering has a significant impact on the methodologies we use to develop and maintain computer software that is employed in large automation systems [475, 449] (the discussion here is based on [449, 72]). Moreover, of course, ideas from theoretical computer science (e.g., some work in automata theory) and AI [444, 387, 136] are sometimes used in the field of control systems development, and the relationship to AI was discussed in this chapter.

**Discrete Event and Hybrid System Analysis:** For an introduction to stability analysis of discrete event systems, see [409]. For more information on hybrid systems, see the special issue of the journal [18], the book [19], or [416, 415, 551, 75, 150, 149, 340, 151, 405]. The importance of providing a mathematical definition of autonomy (see Exercise 1.9), and some initial ideas on such a characterization, was first presented by the author in a panel discussion on autonomy at the 1998 IEEE Int. Symp. on Intelligent Control. Note that this definition would be useful in a hybrid systems analysis context, but significant future research is needed in autonomous control systems analysis via hybrid

system methods to determine exactly how (for fun, in Exercise 1.9 you are asked to mathematically define autonomy).

**Biological and Robot Intelligence:** Questions about whether we will be able to implement high levels of human intelligence with computers have been discussed in many contexts and bodies of literature, including psychology, artificial intelligence, and robotics. Some of these discussions get rather philosophical. Others, such as the ones in [368, 11], have an engineering flavor where the focus is on raw computing capabilities, technological progress in automation, and how this is envisioned to rival intelligent human behavior in the future based on current progress for specific highly automated systems. The important conclusion that many reach from these types of studies is that levels of intelligence will be achieved in the near future that compete with humans along many dimensions so “intelligence” can be thought of as a goal, rather than some mystical unachievable functionality that is specific only to human behavior.

**Cognitive Neuroscience and Evolution:** A good introduction to biology is contained in [91] and introductory ideas in human physiology are given in [346]. Other areas that use biomimicry are discussed in [59]. There, the part on the use of DNA for computing is particularly interesting; however, for even more details on molecular computing, see [13, 195].

Under the heading of “cognitive neuroscience,” for convenience, we will group the areas of cognitive psychology, neuroscience, neurobiology, neurophysiology, neuropsychology [318], the psychology of learning, cognitive science, cognitive neuroscience, and others. There is a huge literature in each of these areas. One place that has a nice synthesis of the ideas in these areas that are relevant to the area of intelligent control is in [206, 268]. A detailed treatment of the neuron is given in [312, 268]. There is also a popular literature on how the brain operates, and along these lines the reader may want to consider [421, 122]. To learn more about neuroscience, learning, and evolution of language, see [420].

Skinner’s pigeon example was taken from [106]. More information on the capabilities of humans in performing control tasks, including some discussion on the advantages and disadvantages of using humans or computers and hardware to achieve automation, is given in [538].

Group behavior of organisms is discussed in the areas of swarm intelligence and artificial life [73, 6, 434, 313]. The authors in [73] give a particularly intriguing view of how ant colonies provide the inspiration for the solution to engineering problems. The description of the biology of the *E. coli* bacteria was taken from [342, 384, 8, 87].

Evolution is a field in biology that has a long and rich history. Scientific introductions to evolutionary biology are given in [185, 436] and a brief tutorial introduction is given in [91] and part of the writing in this part was based on that and [348]. For more details on evolutionary game theory, which has close ties to control theory, see [472, 473, 245, 534] (see also the “For Further Study” section at the end of Part V). For an introduction to ideas on how the human brain

evolved, see [206, 162]. Evolutionary impacts of human memory are discussed in [16, 450]. For a readable introduction to the area of evolution, see [139], and the Baldwin effect is discussed there and also in [243, 53, 363].

There is, in fact, a significant amount of popular literature on the topic and much of this is referenced in [139]. Some interesting books include [126, 220] (which are discussed in Exercise 2.3), [127, 128, 129], and other books by Gould mentioned in [220]. A recent interesting perspective, one that is likely to resonate with a system/stability theorist, is provided in [273, 272]. If you are interested in the debate between creationism and evolution, [359] provides a recent study.

This book has its roots in the cybernetic tradition. Early references in cybernetics by Weiner and others are given in [421]. In cybernetics, in addition to the work of Weiner, the book [26] about the brain and the origins of adaptive behavior (e.g., learning) will likely be quite interesting to a system/stability theorist.

Finally, it is interesting to note that the fields of mathematical psychology and mathematical biology sometimes offer interesting perspectives and useful research to bridge the gap between biological systems and engineering (the mathematical models and analysis help build the bridge).

**Part II**

**ELEMENTS OF  
DECISION MAKING**

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## Sequence of Essential Concepts

- Networks of neurons for motor control used in many animals (e.g., for swimming or walking) are “hard-wired” (i.e., they do not support learning) and hence can be viewed as “instinctual neural controllers.” Computer models of such neural networks can provide sophisticated stimulus-response characteristics that allow them to serve as general-purpose controllers. In biology, the “design methodology” for such hard-wired neural controllers is provided by evolution, while in engineering, we are confronted with the often complicated task of choosing the types and interconnections of the neurons so that they provide appropriate controller functions; this will later motivate the need for automatically learning or evolving neural network parameter values.
- Humans are employed to solve a wide array of feedback control tasks. The fuzzy and expert control methodologies provide two “rule-based control” methods to distill human control expertise into computers (e.g., rules about what actions to take in different situations); they provide methods for “human mimicry.” From a control-theoretic perspective, they provide a heuristic construction procedure for nonlinear controllers. From a biological perspective, they provide a way to overcome the design difficulties for instinctual neural controllers via a convenient vehicle for the exploitation of domain-specific heuristics. They emulate the “software level” of deduction (or “behavioral level” of control tasks) while the neural networks we study emulate the physiological level.
- Humans who perform control tasks often use “mental models” of the environment (problem domain) to plan ahead and to select actions that appear to best lead to achieving their current goals. Controllers that use such planning rely on the use of a model of the plant (e.g., a design model) to predict how the plant will react to different inputs. Then, optimization methods are used to pick the sequence of inputs that best leads to achievement of goals. Finally, the first input (action) from that sequence is input to the plant and the process repeats. Model inaccuracies lead to poor predictions and hence, inputs that may not lead to achievement of goals; however, properly designed controllers use feedback to compensate for the model inaccuracies. Planning strategies provide for very general and widely applicable control and automation methods.
- Attentional systems allow an organism to focus on important information, allocate cognitive resources, and manage information complexity. There



are elements of planning (learning) in attention and vice versa: an attentional system may plan (learn) what to pay attention to, and an attentional system can be used to decide what to plan (learn, respectively). Attentional mechanisms are a foundational component of intelligent systems and they can be employed in neural, fuzzy, expert, planning, and learning systems for control.