Neural Control Engineering: The Emerging Intersection Between Control Theory and Neuroscience

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Citation: Phys. Today **65**(12), 50 (2012); doi: 10.1063/PT.3.1824
View online: http://dx.doi.org/10.1063/PT.3.1824
View Table of Contents: http://www.physicstoday.org/resource/1/PHTOAD/v65/i12
Published by the American Institute of Physics.

accounts as Richard Jeffrey's *Subjective Probability: The Real Thing* (Cambridge University Press, 2004) and John Earman's *Bayes or Bust? A Critical Examination of Bayesian Confirmation Theory* (MIT Press, 1992).

Deutsch and Popper also oppose instrumentalism and physical reductionism but strongly embrace fallibilism. An instrumentalist believes that particular statements or entities are not literally true or real, but primarily useful for deriving predictions about other matters. A reductionist believes that they have explanations couched in the terms of some other subject area, often physics. Fallibilism is the view that our best theories and explanations are or may well be false. Indeed many of the best have already proved not to be strictly true. How then does science progress? Our theories approximate truth, and science replaces falsified theories with ones closer to the truth. As Deutsch puts it, we "advance from misconception to ever better misconception." How that works is far from settled. This seems to make premature Deutsch's apparent dismissal of any role for instrumentalist ideas, and his neglect of pragmatist ones, according to which meaning and truth have largely to do with how statements are used and whether they are useful.

For some of Deutsch's concerns, prematurity is irrelevant. But fallibilism undermines some of his claims—for example, that the quantum multiverse theory is a simple consequence of saying the Schrödinger equation is true and that instrumentalism about the quantum wavefunction has the same defects as a more thoroughgoing instrumentalism about scientific theories. The apparently incompatible accounts of the world given by general relativity and quantum theory and the existence of multiple formulations of quantum theory probably sharpen these points. On these matters, and some others, Deutsch neither gives an adequate overview of current thinking nor does justice to alternatives. The treatment of quantum theory in chapter 12, "A Physicist's History of Bad Philosophy," illustrates this, and the treatment of 20th-century philosophy in the same chapter is close to caricature. With respect to philosophy of science, W. H. Newton-Smith's *The Rationality of Science* (Routledge, 1981) and James Ladyman's *Understanding Philosophy of Science* (Routledge, 2002) could provide a corrective that also puts Popperian thought in context.

The Beginning of Infinity is written clearly and is intended for a general audience. But it is also well worth reading by physicists interested in how our discipline fits into the spectrum of human activity or in questions about the future of humanity. The book is so wide-ranging and dense that evaluating its arguments—many of which seem persuasive—is difficult to do in one reading. But I strongly recommend this sprawling, sometimes frustrating, often engrossing book to readers willing to make the critical and creative effort to understand and evaluate its ambitious and often quite philosophical arguments.

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Neural Control Engineering
The Emerging Intersection Between Control Theory and Neuroscience

Steven J. Schiff
MIT Press, Cambridge, MA, 2012.
$55.00 (361 pp.).
ISBN 978-0-262-01537-0

Steven Schiff's *Neural Control Engineering: The Emerging Intersection Between Control Theory and Neuroscience* is largely concerned with predicting and controlling the dynamics of the brain. The problem involves collecting observations of brain activity and filtering out noise and measurement errors.

Issues related to brain dynamics are addressed in perhaps the most interesting part of the book—its final five chapters. Chapter 9 covers Apostolos Georgopoulos's discovery in the 1980s that the direction of a monkey's limb movement is uniquely predicted by the activity of a relatively small population of neurons in the motor cortex. Each of the neurons is tuned to respond optimally for a preferred direction of limb movement, and the vector sum of the neural population activity drives the intended movement. A corresponding effect occurs in the primate visual cortex: The vector sum of the activity of a relatively small population of visual-cortex neurons accurately represents the local orientation of the edge of an object in the visual field. Such findings were seminal for the development of brain–machine interfaces—for example, implanted arrays of microelectrodes. The resulting deluge of data generated by the arrays required much assimilation via so-called Kalman filters.

Chapter 10 provides an interesting introduction to Parkinson's disease and the models developed at the turn of this century by David Terman and colleagues. Their approaches, using simplified Hodgkin–Huxley models, are a first attempt to model Parkinson's disease and provide insight into the efficacy of deep brain stimulation. Chapters 11 and 12 give a brief look at the use of electric fields to stimulate the brain and at recent attempts to understand and control epileptic seizures. The final chapter, 13, is more speculative but raises the possibility that brains themselves implement Kalman filters.

Processing noisy data has its origins in Gauss's 200-year-old least-squares method to minimize the effects of measurement errors. However, the current methods are offshoots of theories developed in the 1930s and 1940s by Norbert Wiener and Andrey Kolmogorov. Those theories minimized the effects of noise and measurement errors from data. Wiener's theory considered continuously changing data that were represented with Gaussian statistics in stationary random processes; Kolmogorov studied very similar processes, but considered data sampled at discrete times.

The problem with both theories was that they dealt only with linear, stationary, and Gaussian processes. It took another 20 years before Rudolf Kálmán in 1960 introduced his filter theory to deal with noisy dynamical systems; it took another 40 years or so before Kalman filter techniques were used to estimate the parameters of equations describing neural activity.

Neural Control Engineering is the first comprehensive account of the most recent developments. Schiff is perhaps uniquely qualified to write it: He is a practicing neurosurgeon, a computational neuroscientist, and a pioneer in the application of control techniques to problems such as chaos. The book's early chapters provide a brisk introduction to least-squares minimization and its connection with Bayes's rule, and thence to processes that incorporate measurements into models of neural activity. In particular, Schiff presents the Kalman filter approach for discrete data, and the Kalman–Bucy filter for continuous data. The first specific neural examples the book considers are the

Hodgkin–Huxley equations that model the ionic currents that trigger electrical pulses in neurons, and various simplifications, such as the FitzHugh–Nagumo equations. Schiff shows that such simplified models often lead to effective controls of neuronal activity.

Chapter 6 deals with a population model of large-scale neuronal activity, the Wilson–Cowan equations, which Hugh Wilson and I developed in the early 1970s. That model is essentially a spatiotemporal extension of equations like FitzHugh–Nagumo, and Schiff shows how a Kalman filter approach can be efficiently used to control the dynamics of circuits described by FitzHugh–Nagumo type equations. Chapters 7 and 8 deal with the construction of ab initio models and filters based directly on data assimilation and with model inadequacies. Chapter 7 discusses the utility of techniques that take data and abstract from it uncorrelated, linear sets that carry the essential information in the original data; those sets can then be used in a Kalman filter approach. Included examples illustrate applications to image analysis, both static and dynamic, and to the analysis of spatiotemporal brain activity.

I found *Neural Control Engineering* to be extremely interesting and well written. I have only two minor caveats. There is too little about the Wiener–Kolmogorov filters. And in chapter 11, the technique of reducing the resistive tree structure of a neural dendrite to an equivalent cylinder is introduced with no citation of Wilfrid Rall's 1950s introduction of the method—Rall's approach is based on impedance matching. Apart from those caveats, the book is a gold mine for anyone interested in learning how to model—and control—brain activity.

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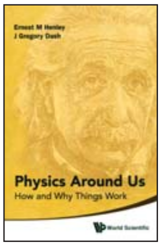
Physics Around Us
How and Why Things Work

Ernest M. Henley and
J. Gregory Dash
World Scientific, Hackensack, NJ,
2012. $34.00 (384 pp.).
ISBN 978-981-4350-63-1

The Transition School at the University of Washington each year offers courses to as many as 16 talented middle school students to prepare them for direct entry into university classes. Among those offerings is a one-year, algebra-based, introductory physics course that was taught by Ernest Henley and the late J. Gregory Dash. The contents of that course now appear as a short textbook, *Physics Around Us: How and Why Things Work*.



When compared with most introductory texts covering the same subject, *Physics Around Us* has two big pluses: Listed at $34, it is cheap; coming in under 400 pages, it is short. The widely used algebra-based text *College Physics* (eighth edition, Brooks/Cole, 2009) by Raymond Serway, Chris Vuille, and Jerry Faughn is more than 1100 pages long and is listed at $285. A large market probably exists for short, inexpensive textbooks such as *Physics Around Us*.

Unfortunately, though, as much as I wanted to like the book, I cannot recommend it. *Physics Around Us* has a lot of errors. Most of them are small, but they are troublesome nonetheless. The worst error appears early in the book, on pages 47–48, in the discussion of an object falling through a fluid. The authors write, "A falling body is acted on by both gravity and air resistance, so the acceleration a is given by $ma = mg - kv$. Since $v = at$, we have: $ma = mg - kat$."

As Physics Today readers will realize, that is wrong. The authors assume a formula for velocity that is correct only for constant-acceleration motion. They use the incorrect expression for velocity to derive an incorrect formula for acceleration as a function of time. I realize that the textbook is for students who haven't taken calculus, but it would be much better to simply state the correct result without proof than to use faulty mathematics to get the wrong one.

In the same discussion, the authors state that at very low speeds, the resistance of an object in a fluid is proportional to the velocity. That is the form of drag force that they consider in the text. While that is true in the low Reynolds number regime, in most real-world cases the drag force is proportional to velocity squared. If you take that more realistic approach, you can derive the correct expression for terminal velocity without using calculus by equating the drag force with the weight of the falling body. The bonus is that it also shows how terminal velocity depends on fluid density, mass, and surface area. There's a lot more physics in that approach than the approach taken by the authors.

Space prevents me from discussing all the errors, but there are enough that