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Biophysical Mosaic of the Neuron

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Introduction

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In this article we broadly review the biophysical mechanisms of neurons that are likely to be relevant to computational function (Table 1). These mechanisms operate within the complex three-dimensional anatomy of the single neuron and are manifested by electrical and chemical interactions between ions on either side of the cell membrane and the diverse proteins and other molecules embedded in the membrane and within the cytoplasm (Figure 1). The signals mediating these interactions may be defined by the voltage across the cell membrane or by concentrations of specific molecules in specific conformational or metabolic states. The first case relies on the voltage sensitivity of various membrane proteins; the second relies on a vast multitude of receptor proteins that link the functional state of neuronal proteins with the external or internal concentrations of ions and molecules.

It may be noted that none of these cellular mechanisms is unique to neurons. For example, essentially all the mechanisms discussed in this article may be relevant when considering a possible computational role of the neuroglia network (Laming et al., 2000). By the same token, neurons (and glial cells) include the essential mosaic of biochemical systems found in all cells required for metabolism, reproduction, growth, and repair. The complexity is daunting. Here we focus on the better-known elements most clearly linked to the reception, processing, and transmission of neuronally represented information. It may seem that there are so many such elements, and an even larger number of unknown relationships, that it would not be possible for a model to take all of the actual dynamic behaviors into consideration. Nevertheless, it also seems likely that an oversimplification of these interactions—for example, in the extreme case by describing single neuron function as an abstracted trigger device—may put fundamental limits to the explanatory and predictive power of any neural model. The challenge remains, then, to develop a description of single neuron function that can serve as the foundation for a practical yet sufficient neural theory.

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We start with a metaphor, the mosaic neuron. A *mosaic* is a collection of discrete parts, each with unique properties, fitted together in such a way that an image emerges from the whole in a nonobvious way. Similarly, the neuronal membrane is packed with a diversity of receptors and ion channels and other proteins with a recognizable distribution. In addition, the cytoplasm is not just water with ions, but a mosaic of interacting molecular systems that can directly affect the functional properties of membrane proteins. Whether for the developing or for the mature neuron, this mosaic is not stationary. To begin with, neuronal proteins are constantly recycled, as is the case for all cells. Furthermore, on both long and short time scales, most mechanistic theories for learning and memory implicate physical changes in various cellular constituents. On time scales of seconds or less, different signaling systems impinging on the neuron from the network or present in the cytoplasm can modify the properties of the mosaic elements, and in some cases their distribution within the cell (see ACTIVITY-DEPENDENT REGULATION OF NEURONAL CONDUCTANCES). Thus, just as a mosaic painting provokes perception of a complete image out of a maze of individually diversified tiles, current thinking holds that a given neuron performs a well-defined computational role that depends not only on the network of cells in which it is embedded but also to a large extent on the dynamic distribution of macromolecules throughout the cell.

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The Minimal Essential Model and the Biophysical Mosaic

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It remains an open question as to what constitutes a minimal neuron

67 model for reproducing functional neuronal computation (Meunier
68 and Segev, 2000; see also CANONICAL NEURAL MODELS). This is
69 in part because to date, only a handful of neuron circuit models
70 come close to predicting known experimental data in any nontrivial
71 way. The question of finding a minimal model is hardly an aca-
72 demic one, as can be appreciated by reviewing the dimensionality
73 of the mosaic neuron (Table 2).

74 Whatever the minimal essential model turns out to be, a detailed
75 knowledge of neuronal biophysics is most likely necessary for un-
76 derstanding the system behavior (even if this understanding is not
77 sufficient). The clearest evidence for this point of view comes from
78 psychopharmacology: although we lack a clear understanding of
79 the mechanisms, we know that adding certain chemicals to the
80 brain parenchyma can qualitatively alter cognitive behavior. We
81 know that the direct action of psychotropic drugs is probably to
82 change one or more biophysical properties at the microscopic cel-
83 lular level, such as blocking an ion channel, altering the binding
84 kinetics of a receptor, modulating a biochemical pathway, and so
85 on, rather than acting at a more macroscopic systems level, such
86 as cleanly disconnecting a circumscribed subcircuit from the entire
87 network. We know that physical access to the brain is necessary
88 for this action (preventing a drug from crossing the blood-brain
89 barrier eliminates its effect), and we also know, in many cases, that
90 some neurons have highly specific membrane receptors for a given
91 psychotropic molecule that are often localized in very restricted
92 areas at the level of brain substructures and even at the single-cell
93 level. Often there is direct evidence of a drug's effect in electro-
94 physiological measurements of single cells, when a change in in-
95 trinsic response properties or synaptic dynamics is seen after a
96 given chemical is added to the fluid bathing the nervous tissue.

97 **The Mosaic's Tiles**

98 We will now review the major proteins that compose the neuron
99 mosaic and discuss some basic implications of their diversity and
100 complexity. These macromolecules include ion channels, receptors
101 (described along with the molecules that activate them), enzymes,
102 gap junctions, pumps, exchangers, and transporters. Note that these
103 classifications can sometimes overlap. For example, an ionotopic
104 receptor is a protein multimer that includes both a receptor part and
105 a channel part.

106 Several texts may be consulted for more detail on these mech-
107 anisms (Johnston and Wu, 1995; Weiss, 1996; Koch and Segev,
108 1998; Fain, 1999; Hille, 2002). In particular, the textbook by Koch
109 (1999) provides an explicit foundation for the computation/
110 algorithm/implementation trinity that is fundamental for under-
111 standing brain function.

112 *Ion Channels*

113 Ion channels are membrane-spanning proteins that, owing to their
114 conformational states, which allow the passage of ionic current, are
115 the primary basis for the dynamical electrical behavior of neurons
116 (see ION CHANNELS: KEYS TO NEURONAL SPECIALIZATION). The
117 permeability of the conducting states and the kinetics governing
118 state transitions (generally referred to as channel gating) can be
119 affected by a variety of factors, principally the membrane voltage
120 and the intra- and extracellular concentrations of the permeable ions
121 and other specific molecules. Sensitivity to extracellular molecules
122 is generally mediated by either direct action on the channel or vari-
123 ous receptor proteins (e.g., in response to neurotransmitters), as
124 discussed below. Molecules that affect channel gating from the
125 inside include second messengers. The kinetic relationship between
126 membrane voltage, the concentration of neurotransmitters, second
127 messengers, and a channel's conductance state can be quite com-
128 plex, a point we return to later.

129 Since channels are the most direct mechanism determining the
130 basic firing properties of the cell (e.g., regular adapting, bursting,
131 fast spiking), and since channels are subject to functional modu-
132 lation on a variety of time scales, it is not surprising that a given
133 neuron can exhibit more than one "stereotypical" firing behavior,
134 depending on the conditions (see NEOCORTEX: BASIC NEURON
135 TYPES).

136 *Receptors and Their Agonists and Antagonists:*
137 *Neurotransmitters, Neuromodulators, Neurohormones,*
138 *and Second Messengers*

139 Receptors are membrane proteins whose functional action is trig-
140 gered by the reversible binding of specific molecules called ligands
141 (Cooper, Bloom, and Roth, 1996; see NMDA RECEPTORS: SYN-
142 APTIC, CELLULAR, AND NETWORK MODELS). A given molecule
143 may be a ligand for more than one kind of receptor, with very
144 different or even opposite functional effects; likewise, a given re-
145 ceptor may be able to be activated by more than one endogenous
146 (or artificial, that is, experimental or pharmaceutical) ligand. A li-
147 gand that tends to upregulate the functional activity of a receptor
148 protein is called an agonist for that receptor. Conversely, antago-
149 nists are molecules that inhibit the activity of a receptor.

150 There are two basic types of receptors, ionotropic and metabo-
151 tropic. Ionotropic receptors are directly associated with an ion
152 channel whose gating is controlled by the presence of the receptor
153 agonist. The action of metabotropic receptors is more complex:
154 upon binding to an agonist, these receptors activate a G protein (so
155 named because their action involves the conversion between guan-
156 osine diphosphate and guanosine triphosphate), which may directly
157 control channel gating or may initiate a biochemical cascade medi-
158 ated by second messengers. The end point of this "chain reaction"
159 can be, for example, the opening of a channel, or the phosphory-
160 lation of a receptor by the activation of a kinase.

161 Agonists are properly called neurotransmitters when released by
162 the presynaptic terminal of an axon (or possibly a dendrite) arising
163 from another neuron (see NEOCORTEX: CHEMICAL AND ELECTRICAL
164 SYNAPSES). Extracellular agonists also include neuromodula-
165 tors and neurohormones, with the latter distributed through the vas-
166 culature as well as the perineuronal space (see NEUROMODULATION
167 IN MAMMALIAN NERVOUS SYSTEMS and NEUROMODULATION IN
168 INVERTEBRATE NERVOUS SYSTEMS). From a functional viewpoint,
169 the main difference between these agonists and neurotransmitters
170 is that neurotransmitters generally mediate synaptic communica-
171 tion between two specific pre- and postsynaptic cells, whereas the
172 release of a neuromodulator or neurohormone into the extracellular
173 space mediates *pancrinic* transmission, affecting a local region of
174 tissue rather than a single postsynaptic site. Another, somewhat
175 arbitrary, difference is that neuromodulators and neurohormones
176 tend not to overtly excite or inhibit their targets, but rather shape
177 the response of a neuron to classical synaptic transmitters in various
178 and subtle ways (Kaczmarek and Levitan, 1987). Note that a given
179 molecule can be assigned more than one of these roles (e.g., neu-
180 rotransmitter versus neuromodulator), depending on the cell type
181 or region in the nervous system.

182 Intracellular second messengers are called such because their
183 concentration is often subsequent to the message delivered by neu-
184 rotransmitters (e.g., after activation of a metabotropic receptor).
185 Second messengers may have direct actions or, as mentioned, may
186 participate in more complicated reaction schemes. Depending on
187 the complexity of the reaction, the functional action of second mes-
188 sengers can be quite delayed and last for minutes if not longer. In
189 addition, the more complicated the biochemical cascade, the more
190 opportunities there are for interactions with modulatory pathways.

191 The most well-known second messenger is the Ca^{2+} ion, which
192 modulates various membrane channels and biochemical cascades,
193 including many neurotransmitter release systems, and whose intra-
194 cellular concentration is mediated by a variety of Ca^{2+} -permeable
195 channels, pumps, buffers, and intracellular stores (involving as well
196 the extensive endoplasmic reticulum network, which may support
197 regenerative intracellular Ca^{2+} waves [Berridge, 1998]).

198 There is a vast array of receptor types, some of which are as-
199 sociated with classical point-to-point synaptic transmission, others
200 that mediate *pancrinic* transmission, and still others that function
201 as links along intracellular pathways. Presynaptic membrane may
202 also express extracellular receptors whose agonist is either the
203 transmitter released by the same terminal (and thus implementing
204 an immediate feedback loop) or another substance, which then may
205 modulate the presynaptic terminal properties. A given neuron may

206 express many different types of receptors in response to the sig-
207 naling molecules released from other cells, normally in a nonuni-
208 form distribution over its surface. In contrast, the number of neu-
209 roactive compounds that a single neuron releases itself is usually
210 one, probably (according to current knowledge) at most two or
211 three.

212 *Enzymes*

213 Among the wide variety of enzymes distributed in the neuron's
214 cytoplasm, the most important types for signal processing include
215 kinases and phosphatases, as well as those involved in the metab-
216 olism of signaling molecules (e.g., synthases and lipases). The ki-
217 nases and phosphatases respectively phosphorylate (add a phos-
218 phate group) and dephosphorylate specific target proteins, as a
219 result modifying the functional properties of the target. This is the
220 most common mechanism of regulating the activity of neuronal
221 proteins, for example, by altering the responsiveness of a receptor
222 to an agonist, or the voltage dependency or conductance of an ion
223 channel.

224 *Gap Junctions*

225 Gap junctions are membrane proteins that form a direct electrical
226 path between two neurons, essentially as a nonlinear, nonselective
227 ion channel (see NEOCORTEX: CHEMICAL AND ELECTRICAL SYN-
228 APSES). Thus, on the one hand, these connections are like conven-
229 tional synapses in that they mediate information flow from cell to
230 cell, but on the other hand, they are quite unlike conventional syn-
231 apses in that this flow is (more or less) reciprocal and instantaneous.
232 As with essentially all the other neuronal elements, gap junctions
233 can be functionally modulated, typically by Ca^{2+} or other second
234 messengers.

235 *Pumps, Exchangers, and Transporters*

236 Pumps, exchangers, and transporters are membrane proteins re-
237 sponsible for the active maintenance of concentration gradients of
238 different ions and molecules crucial for neural signal processing,
239 and thus are able to modify the membrane potential, either directly
240 or indirectly.

241 For example, the enzyme Na/K ATPase maintains the charac-
242 teristic Na^+ and K^+ gradients across all cell membranes; related
243 proteins include the calcium and proton pumps. The action of these
244 pumps depends on the hydrolysis of adenosine triphosphate (ATP)
245 to adenosine diphosphate (ADP), and thus they are tightly coupled
246 to the metabolic machinery of the neuron. Since these cations di-
247 rectly or indirectly contribute to the membrane potential, and since
248 the kinetics of the pump can be modulated, a pump can set the
249 neuron's long-term electrical behavior.

250 In addition to driving channel currents, the Na^+ and K^+ gradi-
251 ents across the cell membrane also provide the energy for exchang-
252 ers and transporters. Exchanger proteins move ions such as Ca^{2+}
253 and protons out of the neuron, against their gradients, in exchange
254 for Na^+ moving down its gradient. The exchangers react faster than
255 pumps and thus provide early protection against excessive accu-
256 mulation of various ions. Transporter proteins move molecules
257 such as glutamate and GABA (respectively the principal excitatory
258 and inhibitory neurotransmitters in the central nervous system)
259 back into the neuron (and into surrounding glia as well) after being
260 released into the extracellular space during synaptic transmission.

261 The activity of some of these proteins is electrogenic. For ex-
262 ample, the Na/K pump cycles two K^+ ions in for three Na^+ ions
263 out, and therefore directly generates a net outward current that can
264 cause a hyperpolarization of many millivolts, depending on con-
265 ditions. Although not always inherently electrogenic, there is an
266 indirect link between the activity of exchangers and transporters
267 and the membrane potential. Since they are driven by the inward
268 movement of Na^+ , an increase in exchanger or transporter activity
269 leads to an increase in the cytoplasmic concentration of Na^+ , which
270 will then be countered by increased Na/K ATPase activity and its
271 attendant electrogenic effect.

272 *Implications of Neuronal Macromolecule Diversity* 273 *and Complexity*

274 Channels, receptors, pumps, enzymes, and so on are comprised of
275 one or several individual proteins, called subunits, each of which
276 is coded by a specific gene. For any given type of channel (etc.)
277 there may be many variations of the complete ensemble, or *mul-*
278 *timer*, as one subunit substitutes for another, which often imparts
279 different peculiarities to the functional properties of the multimeric
280 protein (binding sites, effect on kinetics, etc.—in fact, the same sort
281 of properties that may be affected by protein phosphorylation).
282 Thus, a particular Ca^{2+} channel type, for example, may have ten
283 or so identified variants or subtypes (with the strong likelihood that
284 more remain to be discovered). There are as yet but few demon-
285 strations, either by explicit functional studies or by model predic-
286 tion, that these differences between subtypes are relevant for neural
287 computation. Nevertheless, correlations are increasingly being
288 found between particular disease states and subtle functional alter-
289 ations of cellular elements, or, in the opposite sense, functional
290 (e.g., behavioral) expressions of genetic manipulation (e.g., knock-
291 out) protocols. Thus, the reality of subtype diversity suggests an
292 important limitation for models that employ a single stereotypical
293 kinetic model of a given type of neural protein.

294 Subunit substitution in a receptor, channel, or other neural pro-
295 tein can, among other things, determine different endogenous mod-
296 ulatory agonists or antagonists. Since there are many candidates
297 for pancretic pathways at most neurons, this mechanism is impor-
298 tant for understanding circuitry dynamics in the intact brain. This
299 functional diversity also has extremely important implications for
300 clinical pharmacology: different subunits can also impart sensitiv-
301 ities to different exogenous compounds, allowing the eventual pos-
302 sibility of targeting very specific synapses or other cellular ele-
303 ments with the appropriately chosen (or designed) drug.

304 Individual proteins are comprised of contorted chains of thou-
305 sands of amino acids. This fundamental complexity allows for, in
306 principle, several mechanisms by which a protein may be influ-
307 enced by its local environment. Thus, there may be an important
308 location dependence of the functional properties of a particular kind
309 of protein, reflecting subtle variations in the protein's microenvi-
310 ronment. For the same reason, it is not surprising that the behavior
311 of a channel, for example, may be modified by the membrane volt-
312 age or by binding with a signaling molecule. In this context, we
313 may note that quantitative experimental measurements of a given
314 channel or receptor type in different cell types are inevitably dif-
315 ferent, beyond what would be expected from experimental vari-
316 ability. Sometimes such differences are seen even between different
317 locations of a single cell type (in particular somatic versus den-
318 dritic). Thus, there are at least two possible explanations for such
319 differences: they may be intrinsic to the neural protein under in-
320 vestigation (i.e., a difference in subunit composition), or they may
321 reflect how different local environments, specific to different cell
322 types or location within a single cell, can influence the protein's
323 behavior.

324 **Neuron Models and the Biophysical Mosaic**

325 We now return to the question of neuron models and how they
326 might relate to cellular details. In the most general sense, a single
327 neuron provides a dynamic mapping from a spatiotemporal pattern
328 of pulsed inputs impinging on its dendrites and soma, into a single
329 sequence of output spikes at the axon hillock, which may then be
330 further altered by distinct mechanisms in the axonal tree and pre-
331 synaptic boutons. Overall, the neuron models employed by theo-
332 rists describe the time-varying three-dimensional biophysical mo-
333 saic underlying this complex signal processing to varying degrees
334 (see PERSPECTIVE ON NEURON MODEL COMPLEXITY and SINGLE-
335 CELL MODELS).

336 At the simplest level, an extreme abstract model might be a point
337 integrator whose output is passed through a static sigmoid transfer
338 function, where the scalar output is analogous to the firing rate of
339 a spiking neuron. Here the biophysical basis is essentially limited
340 to the resistive nature of the neuron membrane and the spike thresh-

341 old. As a next step, the basic temporal characteristics of neuronal
342 function may be represented by a leaky integrate-and-fire model
343 that captures the resistive-capacitive nature of the neuron mem-
344 brane and the action potential–based point process communication
345 between neurons (see INTEGRATE-AND-FIRE NEURONS AND NET-
346 WORKS). Among other things, this scheme allows for encoding by
347 both firing rate and higher-order statistics of spike trains, as well
348 as a more tractable analysis of generalized stochastic mechanisms
349 (see ADAPTIVE SPIKE CODING, RATE CODING AND SIGNAL PRO-
350 CESSING, and SENSORY CODING AND INFORMATION
351 TRANSMISSION).

352 A more explicit description of biophysical mechanisms might
353 start with the characteristics of membrane channels and dendritic
354 cables (see DENDRITIC PROCESSING). For example, a single neuron
355 model may include transmitter-gated synaptic conductance inputs
356 distributed on a linear (or “passive”) cable tree topology, with
357 conductance-based (i.e., voltage-dependent channels) spike gen-
358 eration at a central somatic node. An anatomically based dendritic
359 cable structure provides an explicit basis for synaptic weights via
360 different coupling impedances to the soma, as well as cable-
361 dependent (e.g., “on-the-path”) nonlinear synaptic interactions.
362 Simple channel models can capture basic spike firing properties
363 such as absolute and relative refractory period, adaptation, or non-
364 zero minimum firing rates.

365 A model with increased biophysical realism could include
366 voltage-dependent membrane properties distributed throughout the
367 cell (Stuart, Spruston, and Häusser, 1999; see DENDRITIC PRO-
368 CESSING). Intrinsic and synaptic mechanisms can be modeled with
369 less or more sophisticated kinetic descriptions, either deterministic
370 or stochastic (see TEMPORAL DYNAMICS OF BIOLOGICAL SYNAP-
371 SES, SYNAPTIC INTERACTIONS: KINETIC MODELS, and SYNAPTIC
372 NOISE AND CHAOS IN VERTEBRATE NEURONS). Further details of
373 functional properties may require descriptions of the microphy-
374 siology of extra- and intracellular systems, and thus explicit mod-
375 eling of biochemical dynamics, including Ca^{2+} diffusion, buffer-
376 ing, sequestration, and release; protein conformations; and enzyme
377 activation/inactivation. Finally, the most faithful cellular model
378 would require a four-dimensional construct whose biophysical
379 properties vary with both space and time, in particular depending
380 on past activity, or “experience” (see HEBBIAN SYNAPTIC
381 PLASTICITY).

382 State Variables and Functional Compartments 383 of the Mosaic Neuron

384 The many cellular elements we have described suggest a similar
385 number of variables that characterize the functional state of a neu-
386 ron as a signal processing device, each of which may be thought
387 of as representing information. The most classical variable, of
388 course, is the membrane voltage, which defines the immediate in-
389 tegration of synaptic input onto the dendritic tree and soma and,
390 eventually, the action potential output of the cell. However, it may
391 be argued that for predicting spike output, the first derivative of
392 the membrane voltage may be nearly as important as the actual
393 value of the voltage, a behavior that is easily predicted by Hodgkin-
394 Huxley-type models (see AXONAL MODELING and ION CHANNELS:
395 KEYS TO NEURONAL SPECIALIZATION). Other variables that may
396 be important include the concentration of ions and various neu-
397 roactive molecules (e.g., transmitters and second messengers) both
398 inside and outside the cell, and the metabolic or conformational
399 state of various membrane and intracellular proteins. Finally, it may
400 be useful to consider structural or anatomical parameters of the
401 single neuron as functional state variables, such as number and
402 distribution of spines or postsynaptic sites.

403 All of these state variables are determined by complex relation-
404 ships between the cellular constituents. For example, the membrane
405 voltage at any given point in the neuron is determined by the spatial
406 distribution of electrically conducting membrane channels and their
407 reversal potentials, the membrane capacitance, and the electrical
408 coupling to the rest of the cell as determined by the three-
409 dimensional branching cable structure and cytoplasmic resistivity.
410 In turn, the ion concentration gradients that underlie channel re-
411 versal potentials are determined by an interplay between the cur-

412 rents through the appropriate channels (which tend to reduce the
413 gradients) and membrane pumps, exchangers, transporters, and in-
414 tracellular buffer and sequestering systems (which in general tend
415 to maintain the gradients). Finally, in some cases ions passing
416 through a given membrane channel can subsequently bind with and
417 then modulate the conduction state of either the same or possibly
418 other types of channels. Clearly, feedback pathways are the rule
419 rather than the exception in the mosaic's interactions (see Figure
420 1).

421 The state variables of a neuron can be associated with a variety
422 of functional compartments, with spatial scales that range from less
423 than a micron to the entire cell. These compartments may corre-
424 spond to the spatial gradients of voltage (e.g., as determined by
425 dendritic cable properties) or second messenger concentration (e.g.,
426 determined by diffusion constant and geometry of the intracellular
427 space), or to the localization of a given biochemical pathway, or to
428 an explicit subcellular structure (e.g., a dendritic spine, an organ-
429 elle, the cell nucleus). In summary, for most state variables the
430 neuron is far from a classical "well-mixed" system. Rather, an ex-
431 treme internal heterogeneity is usually the case: a single cell thus
432 becomes a cell of cells.

433 *Emergent State Properties of Intracellular* 434 *Chemical Systems*

435 Recent work has demonstrated the possibility of various stable ar-
436 rangements between the concentrations of certain intracellular mol-
437 ecules or the metabolic states of certain proteins, all of which in
438 turn can participate in various biochemical pathways, including
439 those regulating membrane properties and plasticity (Weng, Bhalla,
440 and Iyengar, 1999). From an information processing viewpoint,
441 these combinations can be thought of as essentially distinct states
442 that partially define the functional input/output properties of the
443 neuron. It has also been proposed that changes in cellular properties
444 on even longer time scales may be due to self-stabilizing confor-
445 mational states of proteins such as CAM kinase II or others. Of
446 course, any mechanism underlying a long-lasting modification of
447 the neuronal transfer function is a candidate for the molecular basis
448 of memory (see INVERTEBRATE MODELS OF LEARNING: *APLYSIA*
449 *AND HERMISSENDA*).

450 **Discussion: How Much Biophysics Needs to Be Known** 451 **for a Compelling Brain Theory?**

452 Where does the complexity of the mosaic neuron leave us in terms
453 of formulating a theory for the brain? In particular, how detailed
454 does a model of the neuron have to be, and how does the power of
455 current methods compare with the computational complexity in-
456 herent at various levels of biophysical description? These open
457 questions have a very practical importance, since there are few
458 opportunities for formal analyses of these nonlinear dynamical sys-
459 tems. Furthermore, the increasing experimental knowledge of neu-
460 ronal cellular mechanisms is daunting. The details seem to have an
461 almost fractal quality; no matter what level is being examined,
462 underneath any given mechanism there is another Pandora's box
463 of parameters waiting to be described. Today, so many biophysical
464 properties are known to be present in the neuron membrane that
465 the biggest risk is to choose to include only those that will give the
466 model the properties desired. This leads to a model that is unlikely
467 to fail, and therefore unlikely to teach us anything that we did not
468 know before.

469 The brute force strategy is to construct a bottom-up, biophysi-
470 cally detailed cell model in order to cover as much as possible the
471 high-order interactions between various mechanisms. Once the
472 map has been laid out, sufficiently rich deterministic or stochastic
473 kinetic equations for the membrane elements and intracellular dy-
474 namics may then be assigned. Such maps can be evaluated, at least
475 in principle, since all known biophysical mechanisms can be de-
476 scribed by nonlinear partial differential equations, and thus are
477 amenable to standard numerical integration techniques.

478 However, it may appear that at some point there will be too many
479 equations with too many free parameters for practical evaluation

480 or, more important, for true *understanding*. (On the other hand, the
 481 rapid evolution of computing power suggests that the threshold for
 482 “impractical” is hard to define.) An optimistic view is that once a
 483 sufficiently elaborate biophysical cellular model is constructed, its
 484 behavior may be well enough understood so that a more abstract
 485 model that captures the functional essentials with considerably less
 486 computational expense may be derived. But until there are some
 487 formal criteria for establishing what exactly “essential” means, this
 488 process will inevitably be an iterative one, moving back and forth
 489 between an analysis of detailed cell models in isolation and in
 490 nontrivial networks (limited most probably by the available tools)
 491 and an analysis of more abstract neural networks. The fundamental
 492 challenge to theorists, then, is to go beyond this sort of “reverse
 493 engineering” approach and develop a method that is at once com-
 494 mensurate with the complexity of the brain, yet can produce a bona
 495 fide theory whose detail avoids that of the actual biological reality.

496 **Roadmap:** Biological Neurons and Synapses

497 **Related Reading:** Activity-Dependent Regulation of Neuronal Conduc-
 498 tances; Adaptive Spike Coding; Axonal Modeling; Dendritic Processing;
 499 Hebbian Synaptic Plasticity; Ion Channels: Keys to Neuronal Speciali-
 500 zation; Neocortex: Chemical and Electrical Synapses; NMDA Recepto-
 501 rs: Synaptic, Cellular, and Network Models; Rate Coding and Signal
 502 Processing; Synaptic Interactions: Kinetic Models; Synaptic Noise and
 503 Chaos in Vertebrate Neurons; Temporal Dynamics of Biological
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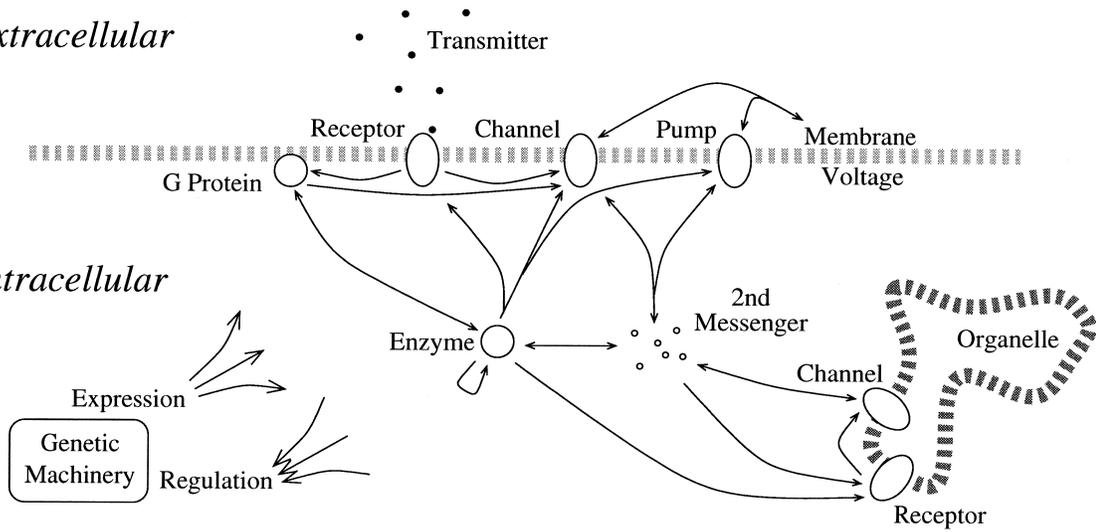
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541 **AQ 1: Author: None of the other articles have these long**
542 **lists**
543

546

Extracellular

Intracellular



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Figure 1. Sketch of the molecular circuit underlying the neuron's biophysical mosaic. This caricature outlines the many interrelated control paths among the molecular elements that determine the functional properties of the neuron. For example, activation of an ionotropic synapse starts with the binding of extracellular transmitter to the membrane receptor, which then directly turns on an associated ion channel. Alternatively, activation of a metabotropic synapse is initiated by transmitter binding to a receptor, which

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then activates a G protein, which turns on an enzyme, which raises the concentration of a second messenger, which, finally, activates a target ion channel. Many control pathways are immediately bidirectional: current through an ion channel changes the membrane voltage, which in turn can control the gating of that same channel. Some elements can even control themselves, for example autophosphorylating enzymes.

| | |
|-----|---|
| 552 | Table 1. Biophysical Mechanisms of Neuron's Relevant to |
| 553 | Computational Function |
| 556 | Ion channels |
| 557 | Control by intrinsic signals (membrane voltage, intracellular molecules) |
| 558 | Control by extrinsic signals (extracellular molecules, e.g., released from presynaptic terminals) |
| 559 | Receptors |
| 560 | Ionotropic: Direct control of ion channels |
| 561 | Metabotropic: Indirect control of ion channels and other internal systems |
| 562 | External binding sites (synaptic and pancreatic) |
| 563 | Internal binding sites associated with neuronal and organelle membranes |
| 564 | Control of internal biochemical systems |
| 565 | Enzymes (kinases and phosphatases, which determine the state of most proteins; others) |
| 566 | Gap junctions |
| 567 | Pumps, transporters, exchangers (electrogenic and nonelectrogenic) |
| 568 | Organelles |
| 569 | Ca ²⁺ sequestering and release (endoplasmic reticulum, mitochondria) |
| 570 | Protein synthesis and metabolism |
| 571 | Maintenance and modulation of three-dimensional structure (spines, dendritic morphology) |
| 572 | Transmitter sequestering and release (synaptic vesicles) |
| 573 | Cytoplasmic biochemical systems |
| 574 | Transmitter synthesis and degradation |
| 575 | G proteins: Initiate second messenger release after receptor activation |
| 576 | Second messengers: Diffusible molecules linking various stages of internal biochemical systems |
| 577 | Effectors: Targets of second messengers, including channels and enzymes (kinases, phosphatases) |
| 578 | Three-dimensional structure |
| 579 | Macroscopic anatomy (soma, dendritic and axonal trees) |
| 580 | Microscopic anatomy (spines, synaptic junctions, variations in dendritic or axonal dimensions) |
| 581 | "Electrotonic" anatomy (modulated by state of local membrane) |
| 582 | Geometrical synaptic and channel distribution |
| 583 | Functional synaptic localization (e.g., retinotopic, tonotopic) |
| 584 | Computational synaptic localization (e.g., on-the-path interactions, coincidence detection) |

588 **Table 2.** Quantitative Summary of the Neuron's Biophysical Mosaic
589 Relevant to Computational Function

592 Spatial scales (voltage and concentration transients): <1 to thousands of
593 microns

594 Temporal scales

595 Kinetics of gating, binding, and diffusion: <1 ms to seconds

596 Gene expression: days to years?

597 Anatomy

598 Tens to hundreds of dendritic and axonal branches

599 Models of electrotonic structure can require thousands of compartments

600 Synapses and channels

601 Thousands of pre- and postsynaptic sites

602 Five major categories of charge carriers: Na^+ , K^+ , Ca^{2+} , Cl^- , other
(e.g., "cationic," proton, etc.)

603 Tens of types for each category, several of which may be expressed in
a single neuron

604 Receptors and associated agonists (neurotransmitters, second messengers,
etc.)

605 Approximately 30 major types, several of which may be expressed in a
single neuron

606 Possibly tens of identified subtypes for some major receptor types

607 A brute force map of a single neuron would be very large indeed. For
608 example, compartmental models of the dendritic tree can require
609 hundreds or thousands of coordinates, corresponding to spatial scales
610 relevant for representing gradients of membrane voltage or of the
611 concentration of intracellular molecules. A given neuron may have
612 thousands of synaptic inputs, each associated with one of several types of
613 receptors, and the cell membrane can include tens of types of ion
614 channels. Furthermore, the different synaptic receptor and channel types
615 are typically scattered inhomogeneously over the neuron. It is also
616 important to consider the stationarity of the map. For computations over
617 hundreds of milliseconds or less, the map may properly be thought to be
618 static, but at longer time scales it may be necessary to consider a
619 dynamic layout of the mosaic. For another *carte du monde* of
620 computational cellular mechanisms and their spatial and temporal scales,
621 see Figure 21.2 in Koch, 1999.

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