Prising the secrets of energy efficiency out of brains

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Principles of Neural Design,
P Sterling, S B Laughlin
MIT Press due Fall 2012
Neuroscience is BIG
Information Processing in Neural Circuits

• Identified neurons
• In intact circuits
• Relate signals to behavioural performance

Answer
1. What?
2. How?
3. Why?

See
Design
Flies' compound eyes – model systems for analysing neural circuit design
Circuits and signals - fly compound eye

analogue signals
Secret 1

Mix analogue and pulsatile
Hybrid computation (*mixing analog & pulsatile*) contributes to Energy Efficiency

Rahul Sarpeshkar, MIT

Neural Computation 10, 1601-1638

His book *Ultra low power bioelectronics*, C.U.P. 2010

Independently reaches many of the conclusion of my talk

---

stop noise accumulating

use efficient analogue operations to process information directly at nodes (*rich analogue primitives*)
Question

Are brains efficient?
“Joe” with IBM Road Runner Supercomputer (2007)

$10^{15}$ events s$^{-1}$

20 watts

2.36 MW
Allocating

Materials and Space

Electric fish brain

Naked mole rat
Secret 2

Allocate resource according to need
Adaptations that conserve space, materials, time
Minimal rationality
Christopher Cherniak
C elegans (aka “The Worm”)
Efficient layout reduces wiring costs

*High wiring cost*

*Low wiring cost*

After Cherniak, 1992
Segregating neurons according to function reduces wire length

Mitchison 1992
Secret 3

Minimise wiring costs
Brains are wired efficiently
Allocate materials efficiently
Do they need to be
Energy Efficient?
Brains need to be energy efficient because demand is high enough to limit signal traffic.

Major sites of energy use:

- Synapses
- Pyramidal neurons

The energy consumed by cerebral cortex limits cortical signal traffic to 1 – 10 spikes/neuron/sec.

*Attwell & Laughlin 2001*
Distribution of energy costs

spikes (action potentials)

synapses' electrical signals

synapses' chemical signals

maintenance

electrical – expensive
chemical - cheap
Secret 4

Distribute signals sparsely
sparse coding is energy efficient
(after Levy & Baxter, 1996)
Secret 5

Send only what is needed
“The neat packaging of information”
Horace Barlow 1961
redundancy reduction as a goal of early sensory processing
Predictive coding
Srinivasan, Dubs and Laughlin, 1982
THEORY

(Srinivasan, Dubs and Laughlin, 1982)

Predictive coding requires an intensity dependent surround. Take wider samples when input is unreliable (photon noise)
Maximise information coded in a channel limited by dynamic range and noise
(Hans van Hateren, 1992)

MODEL

Input "naturalistic" 1/f statistics

Natural signals → Optics → Adapting filter → Neuron

Photon noise → Intrinsic noise

Limited power
Test model

R1-6

LMC

Very dim

Quite dim

daylight

50 ms

LMC Data Model

Very dim

Quite dim

daylight
Model generalises

Similar redundancy reduction model applied to human vision (Atick & Redlich, in Atick, 1992)

Data points = psychophysical data; Curves = redundancy reduction model
Secret 5

Send only what's needed

• eliminate redundancy
• improve SNR before transmission
• boil information down to "what the destination needs to know, no less, no more"
Secret 6

Match neural resources to natural distributions of signals and tasks. Match components across levels ("symmorphosis")

Redundancy reducing adaptive filter matched to input SNR
Gain adapted to input amplitude distribution
Amplifying signal to fill the response range
HISTOGRAM EQUALISATION

(Laughlin, 1981)
Histogram equalisation at the photoreceptor – LMC synapse

Measurements

Response

Histogram (cum. prob.)

\[ I = 5.5 \times 10^4 \]

\[ I = 5.5 \times 10^5 \]
Equalising the response histogram in *Drosophila* olfactory glomeruli

Bhandawat et al 2007

Figure from Abbott & Luo, Nature Nsci News and Views 2007
Working efficiently within device constraints

electrical signalling
Signal quality in single neurons

basic biophysics – graded responses

Noisy signals

\[ R_{\text{channel}} = 10^{11} \text{ Ohms} \]
\[ E = 10^{-1} \text{ V} \]
\[ R_{\text{load}} = 10^9 \text{ Ohms} \]

Small signals  Slow signals  Decaying signals

\[ C_m \text{ is significant} \]
\[ R_m \text{ is high} \]
More ion channels – better performance

- Response speed (bandwidth)
- Amplitude
- Reliability (SNR)

Energy costs; plus space and materials
Energy takes space
mitochondria in neurons

Gao et al, Neuron 2008, Drosophila medulla
Secret 7

Reduce voltage and increase resistance
Secret 8

send information at the lowest rate

(minimise bandwidth and precision)
More ion channels – better performance

Performance

Number of ion channels

Response speed (bandwidth)
Amplitude
Reliability (SNR)

Energy costs; plus space and materials
Testing for a Law of Diminishing Returns

*bit cost vs capacity (max rate)*

Sarcophaga carnaria

Calliphora vicina

Drosophila melanogaster

Drosophila virilis

The data

Quantum bumps

Response

White-noise stimulus

A

B

C

D. melanogaster

Sarcophaga

1 mV
200 ms

-1 contrast

5 mV
200 ms
Capacity increases with bandwidth and precision

\[ I = \int_{0}^{c_0} \log_2[1 + S(f)/N(f)] \cdot df \]
Larger cells - higher capacities
Big cell are faster and more precise

\[ \log_2[1 + S(f)/N(f)] \]
Membrane model gives energy consumption

Different levels of energy consumption

Total Cost (ATP molecules s$^{-1} \times 10^9$) vs. Effective photons s$^{-1}$

- Big
- Small

Fixed (dark) cost
Bigger cells are less energy efficient
(*they have traded economy for capacity*)
Cost increases out of proportion to capacity

Graph:

- **Total**:
  - Equation: \( y = 1.70x + 4.68 \)
  - \( R^2 = 0.95 \)

- **Fixed**:
  - Equation: \( y = 1.47x + 4.75 \)
  - \( R^2 = 0.99 \)
The Law of Diminishing Returns
How to implement
Send at the lowest rate

Distribute information and processing tasks among parallel low rate channels

- sparse coding, parallel pathways

Only use high speed/precision where it is essential

- small number of high speed/precision streams
- larger number of low speed/precision streams

Massively parallel processing in low rate channels each dedicated to small part of the task
Secret 9

Nanofy!

*(reduce to the irreducibly small)*
Miniaturisation

Dendrites (D) of CA1 pyramidal cells – EM section by Dr J. Spacek, Charles Univ Czech Rep. Visit Synapse Web for more details.
What is this spaghetti?

3 km/mm³

synapse

spike

spike

synapse

pyramidal neurons
A channel noise limit to axon miniaturisation

Aldo Faisal, John White and Simon Laughlin 2005

stochastic axon model
Spontaneous rate increases rapidly with decreasing diameter, below 0.2 µm
To be efficient, brains push down to the molecular limits of information transfer.
Secret 10

Do it with chemistry

(*because ye have flesh*)
The voltage sensitive sodium channel

*a molecular machine*

From Horn, *Nature* 2011
summarising Payandeh *et al*, *Nature* 2011
Protein power

Nano (single molecule) finite state machines switching by conformational changes
G protein cycle for the $\beta_2$AR–Gs complex.

SGF Rasmussen et al. Nature 000, 1-7 (2011) doi:10.1038/nature10361
Receptor-G protein interactions.

SGF Rasmussen et al. Nature 000, 1-7 (2011) doi:10.1038/nature10361

Note: This figure is from a near-final version AOP and may change prior to final publication in print/online
Changing protein nano machine states by changing their energy landscape

- Affinities
- Sensitivity
- Kinetics
- Impulse response
- Permit
- New interaction
- Logic

Bind ligand → Exposed P-sites → Phosphorylated
Protein molecules are flexible and versatile

- Easily fine tuned
  - variable gain amplifiers
  - temporal filters
- Process information
  - coincidence detectors (AND gates)
  - NAND gates
- Assembled into information processing complexes and networks
Fine tuning photoreceptor protein network implements van Hateren's optimum filter

Tune impulse response to SNR (light level)

<table>
<thead>
<tr>
<th>LMC Data</th>
<th>Model</th>
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<tbody>
<tr>
<td>Very dim</td>
<td></td>
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<tr>
<td>Quite dim</td>
<td></td>
</tr>
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<td>daylight</td>
<td></td>
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</table>
Molecular machinery for phototransduction in the fly photoreceptor

Hardie & Raghu, 2001
Networks revealed

The chemical synapse before the molecular neurobiology revolution
The outcome of revolution - promiscuity

Glanzman Curr Biol 2010
Protein potential

- Nano-scale devices
- Receive transduce and transmit signals
- Select, amplify and filter signals
- Rich repertoire of analogue and logic operations
- Form networks that integrate and process signals, therefore
- Control and drive all cellular processes
- Reconfigure networks – demand, history
- Allocate resources – demand, history
Changing sensor sensitivity – day to night

*Locust*

David Williams, *Science* 1982
Chemistry is cheaper than Electronics
Cost of signalling at single cortical spine

Synaptic current flowing through receptor ion channels
200,000 ions, 67,000 ATPs

Post-synaptic Ca transient triggered by G-protein coupled receptors
1000 ions 1000 ATP

Attwell & Laughlin, 2001
A heavy weight chemical signalling network
rod photoreceptors

Fain, Hardie & Laughlin, Current Biology 2010
Energy costs of **electrical** and **chemical** signalling in a mouse rod photoreceptor

*Okawa, Sampath, Laughlin & Fain, 2008*
Secret 11

Mix electronics and chemistry
Getting the mix balance pro and cons

- **Chemistry**
  - versatile
  - computationally powerful
  - economical
  - links all levels
  - slow
  - no universal currency at a node

- **Electricity**
  - less versatile
  - computationally weak
  - expensive
  - isolated (uses chem)
  - fast
  - universal currency, "instantaneous" integration of many to one.