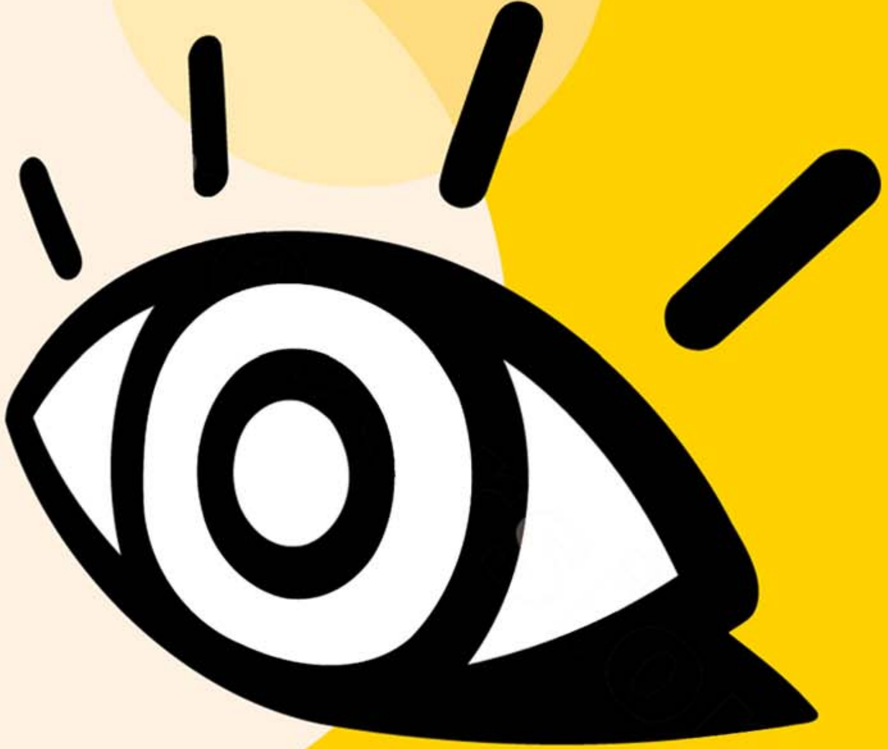
R U B I N

Ready-made Understanding for
Biological Information Processing
in Neuronal Networks



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Explaining Brains by
Educational Simulations

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... seen from the

Educational Stance

1. *Simulations represent exclusive knowledge*

2. *»Explaining brains« is an illustrative example*

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Why Simulation?

Representing Knowledge

- ***declarative***
  e.g. textbooks, database objects

- ***procedural***
  algorithms >> simulations

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a case study:
Neurosciences‘ Simulations ...

... reflect
the brain‘s complexity and dynamic nature

... lead to
(artificial) neural networks

... are applied in
Bionics, Robotics, new ITC, stock prediction

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Why Educational Simulation?

Teacher: *»Chalk & Talk« is inconvenient*

Learner: *Simulations hardly accessible*

>> ***Educational Simulations shall bridge educational gap!***

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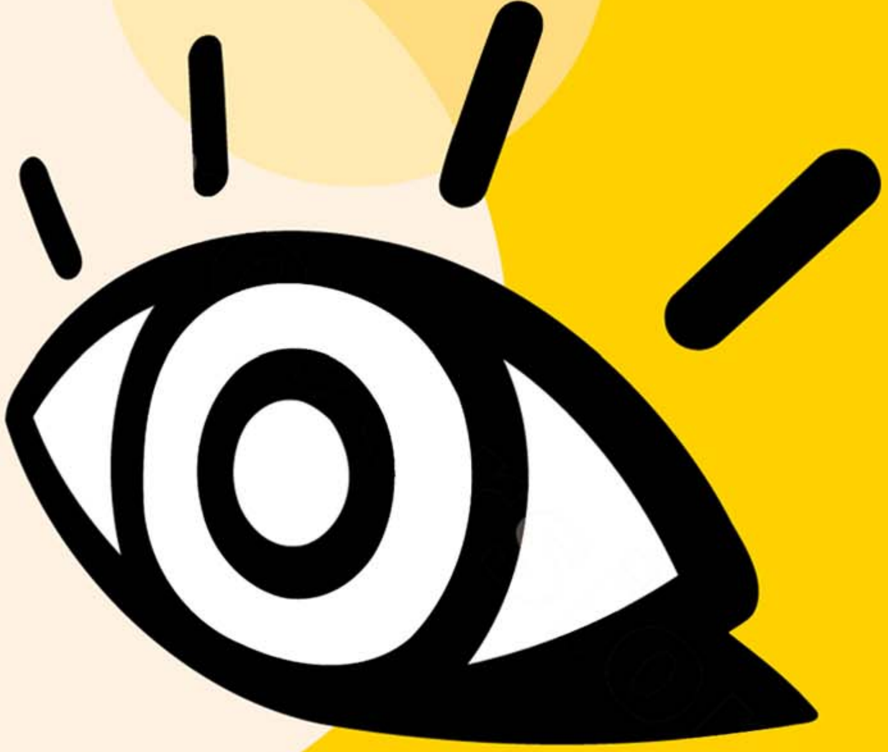

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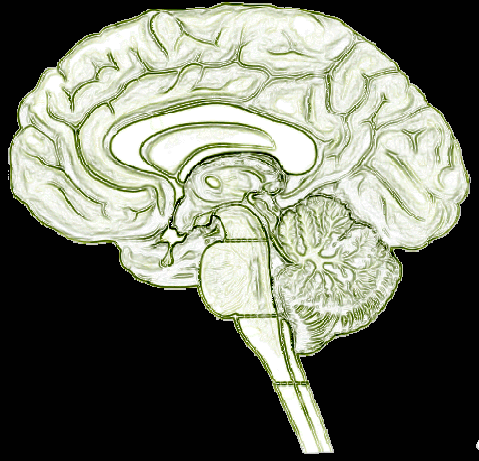
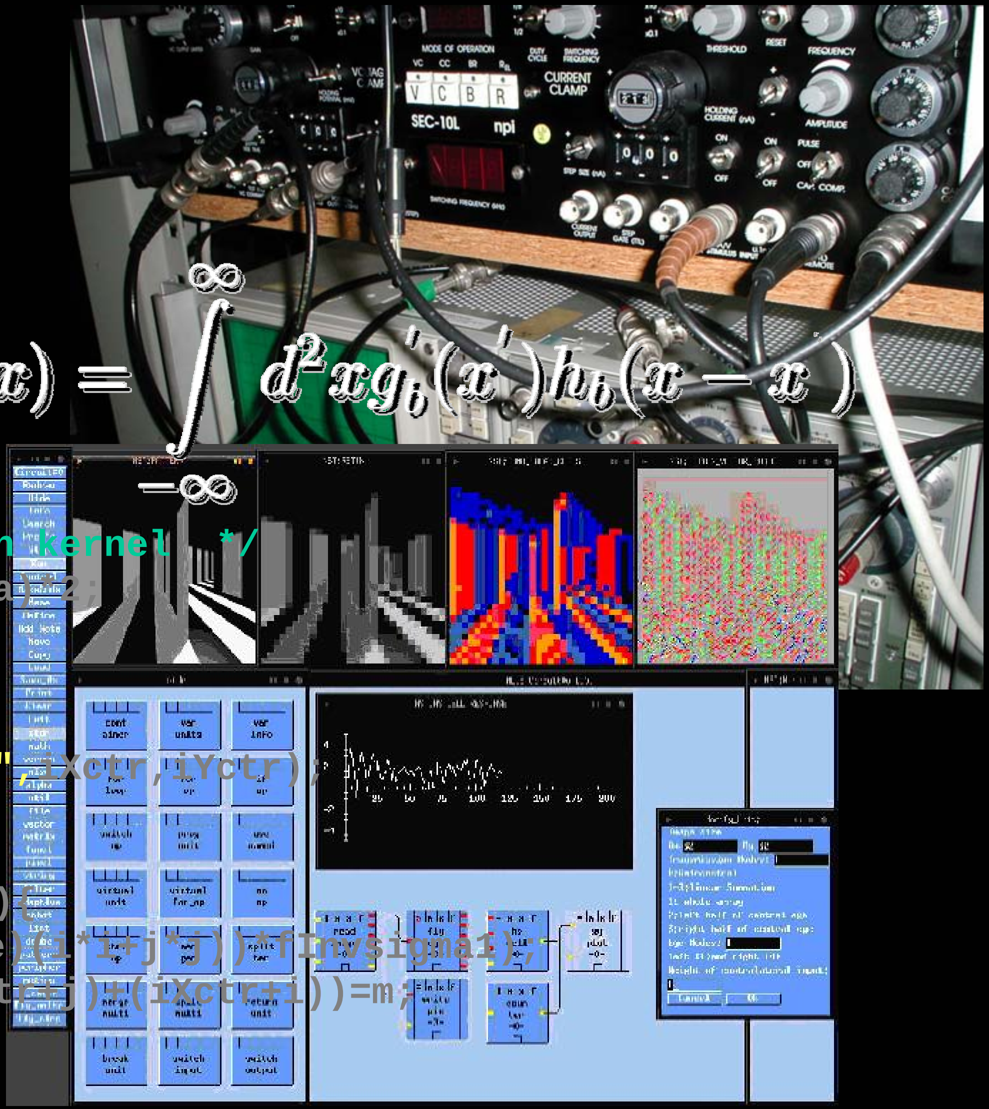
Brains aren‘t easy things to explain...

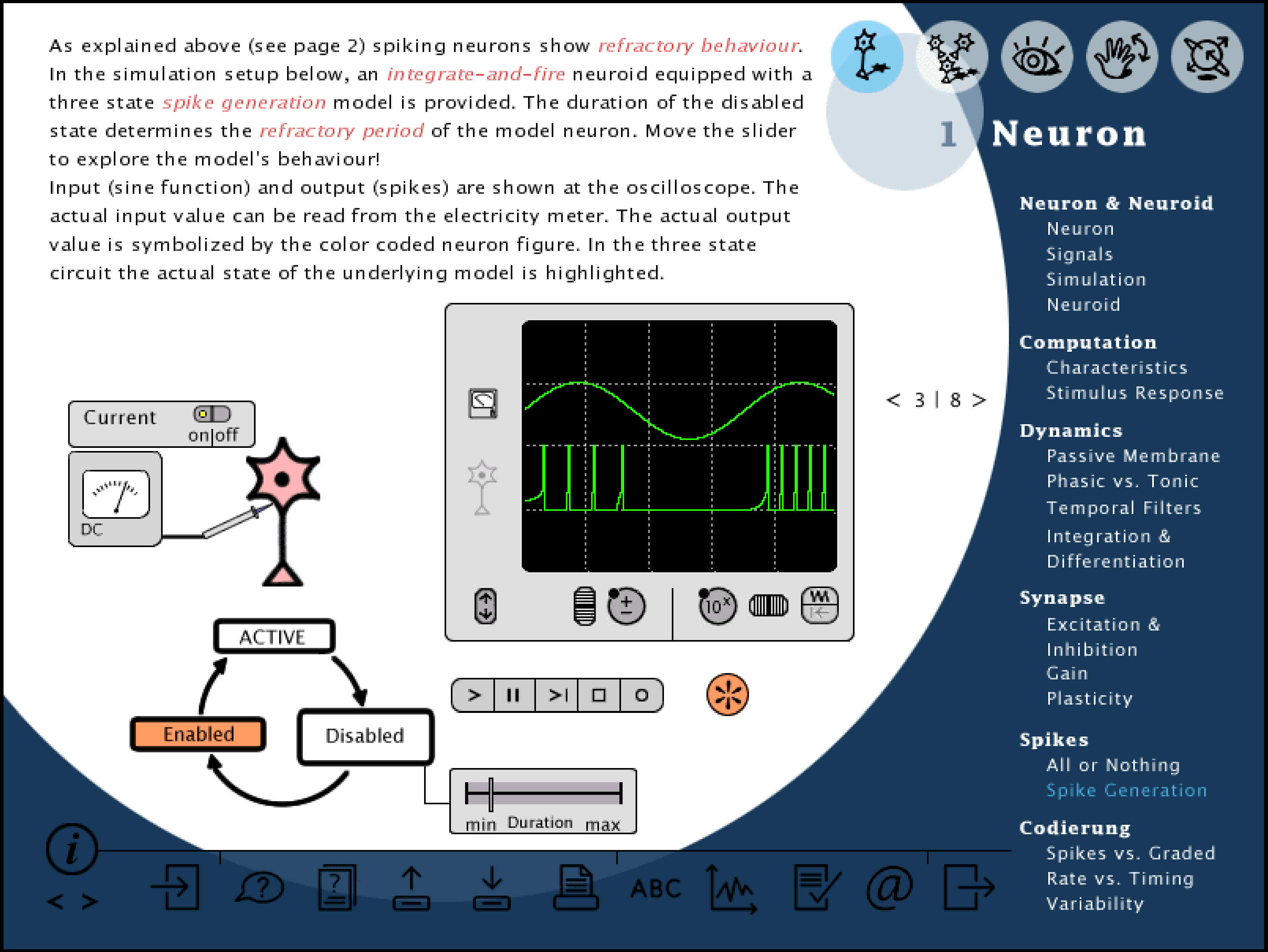




$$g_t(x) \equiv \int_{-\infty}^{\infty} d^2x\, g_t'(x')\, h_t(x-x')$$

```
/* fill mask with Gaussian kernel  */
fSigma1 = (fSigma)*(fSigma)*2;
fInvsigma1 = 1/f Sigma1;
iXctr=(iMdx-1)/2;
iYctr=(iMdy-1)/2;
printf("Xctr:%d Yctr:%d\n",iXctr,iYctr);
fMaskSum = 0.;
  for(j=0;j<=iYctr;j++)
     for(i=0;i<=iXctr;i++){
           m=exp(-((double)(i*i+j*j))*fInvsigma1);
         YP(u,1,iMdx*(iYctr+j)+(iXctr+i))=m;
```

... but it‘s worth trying!



As explained above (see page 2) spiking neurons show *refractory behaviour*. In the simulation setup below, an *integrate-and-fire* neuroid equipped with a three state *spike generation* model is provided. The duration of the disabled state determines the *refractory period* of the model neuron. Move the slider to explore the model's behaviour!
Input (sine function) and output (spikes) are shown at the oscilloscope. The actual input value can be read from the electricity meter. The actual output value is symbolized by the color coded neuron figure. In the three state circuit the actual state of the underlying model is highlighted.

1 Neuron

Neuron & Neuroid
- Neuron
- Signals
- Simulation
- Neuroid

Computation
- Characteristics
- Stimulus Response

Dynamics
- Passive Membrane
- Phasic vs. Tonic
- Temporal Filters
- Integration & Differentiation

Synapse
- Excitation & Inhibition
- Gain
- Plasticity

Spikes
- All or Nothing
- Spike Generation

Codierung
- Spikes vs. Graded
- Rate vs. Timing
- Variability

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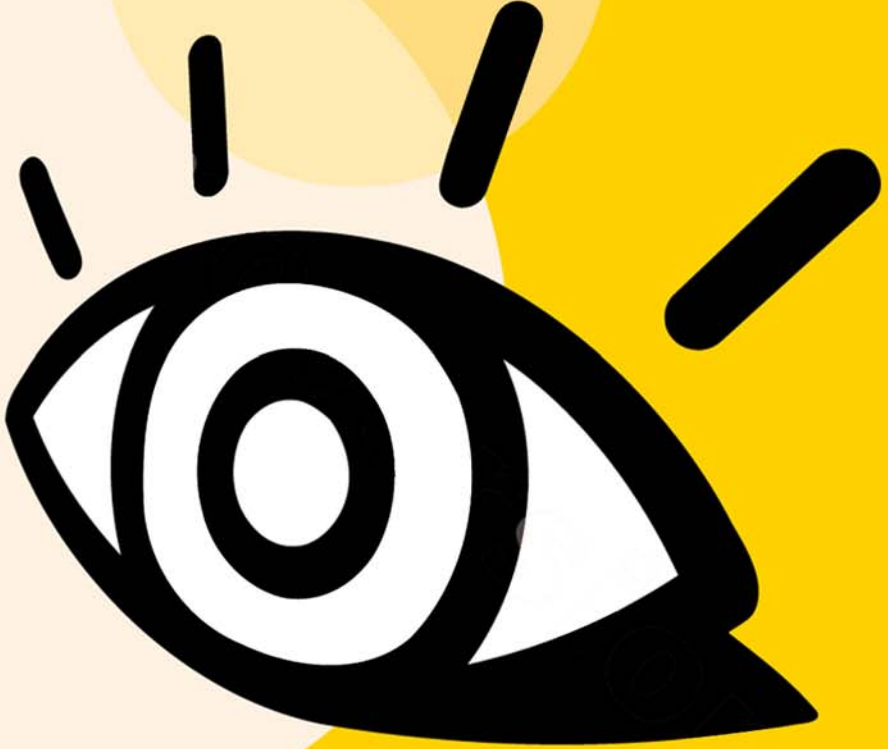

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