

# SpikeNet Documentation

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## 1 Overview

SpikeNet is a software developed for simulating spiking neuronal networks, of which the design provides the following four main features.

**Configurability** SpikeNet supports any user-defined structure of synaptic connectivity topologies, coupling strengths and conduction delays. It can be easily extended by developers to support any variations of integrate-and-fire neuron and synapse models. For the models that are currently available, see [Neuron and synapse models](#).

**Performance** Simulation of spiking neuronal network quickly becomes computationally intensive if the number of neurons  $N$  in the network exceeds a few thousand. To achieve superior performance, various measures have been taken at both algorithmic and implementation level. Notably, at the algorithmic level, kinetic models are exclusively chosen for their algorithmic efficiency (e.g., [2, 4, 8, 9]). Furthermore, for such kinetic models, computational cost of the simulation can be dramatically reduced with the commonly used mathematical abstraction that synapses can be simplified into a few groups, within which their dynamics (or more specifically, the time constants) are identical [1]. At the implementation level, C++, a programming language renowned for its high-performance computing, is used.

**User-friendly interface** In SpikeNet, although, C++ is used for heavy-duty computation, its user-interface is written in a high-level programming language (Matlab) for user-friendliness. This means SpikeNet does not require non-developer users to be familiar with C++. In practise, the typical work-flow of SpikeNet user is as following.

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1. In Matlab, use SpikeNet functions to generate the input files that define the simulation case.
2. Evoke the SpikeNet C++ simulator, which reads the input files, runs the simulation and generates the output files.
3. In Matlab, use SpikeNet functions to parse the output files into Matlab data for post-processing.

Please see [Matlab user interface](#) for more detailed descriptions of the workflow. This design essentially makes the SpikeNet C++ simulator a stand-alone software. Based on these protocols, the C++ simulator can easily interface with any other high-level programming languages if Matlab is not preferred. Developer users will be interested to know that SpikeNet supports HDF5-based input/output file format which follows pre-defined protocols (see [Input/Output protocols](#)).

**Scalability** The design of the SpikeNet C++ simulator readily supports parallel computing used Message Passing Interface (MPI). The simulator has two central C++ classes, representing populations of neurons and synaptic connectivities among these populations, respectively. For example, for a recurrent network consisting of an excitatory neuron population ( $E$ ) and an inhibitory one ( $I$ ), two neuron population objects will be created together with up to four synaptic connectivity objects including  $E \leftarrow E$ ,  $I \leftarrow E$ ,  $E \leftarrow I$  and  $I \leftarrow I$ . These six objects can be created and simulated in parallel and the amount of message passing among them at each simulation time step is minimal. Additionally, HDF5 is supported for handling large input/output data files.

Here are some basic tips on git.

- To get the most recent version of SpikeNet: `git pull origin master`
- Build the new simulator: `make; make clean`
- Avoid directly modifying any existing files in SpikeNet unless you are a developer. Create another directory alongside SpikeNet and put all of your files there. In summary, your project folder should look like:

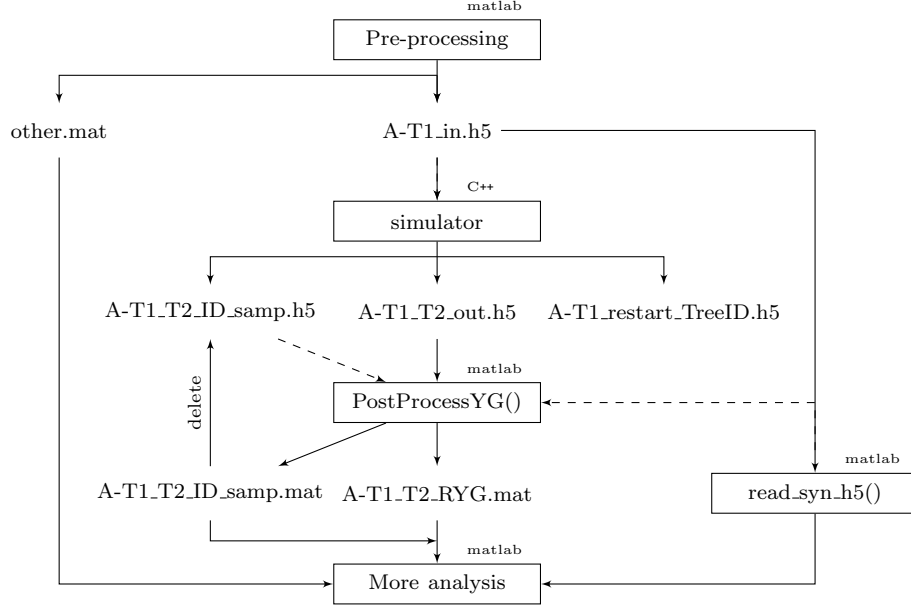
```

tmp
├── SpikeNet
│   ├── cpp_sources
│   ├── matlab_interfaces
│   ├── makefile
│   └── other_scripts
├── simulator
├── tmp_data
├── my_functions
├── PBS_out
└── all_in_one.sh

```

## 2 Workflow

The typical workflow of SpikeNet is as shown in the following flowchart.



Notes:

- Although the C++ simulator accepts input files with any names, A-T1 is the recommended and default naming format. A is a 4-digit PBS array ID number. T1 is a timestamp identifying when the in.h5 file was generated.
- Similarly, T2 is a timestamp identifying when the out.h5 file was generated. Note that T2 allows multiple simulations to be run for the same in.h5 file.
- Similarly, T2 is a timestamp identifying when the out.h5 file was generated.
- The restart\_TreeID.h5 files allow the users to directly modify any aspect of a simulation and restart it from there. The TreeID is automatically generated to ensure that the users can make as many different modifications and restart the simulation as many times as desired.
- For technical reasons, the time series data sampled from each neuron population or synapse group, identified by an ID number, during simulation are stored separately in samp.h5 files.
- The dashed lines mean that the C++ simulator and the PostProcessYG() matlab function will automatically look for those auxiliary input files based on the information contained in the main input files.

### 3 Documentation for the C++ simulator

To view the documentation

- Make sure doxygen and graphviz are installed
- Go to the SpikeNet directory
- Generate the documentation: `doxygen`
- Open the documentation: `open docu*/html/index.html`

### 4 Neuron and synapse models

#### 4.1 Default model

A description of the neuron and synapse models can also be found in a publication that used SpikeNet [3]. The default neuron model in SpikeNet is leaky integrate-and-fire neuron. The membrane potential  $V_i^\alpha$  of the  $i$ -th neuron ( $i = 1, \dots, N_\alpha$ ) from population  $\alpha$  evolves according to

$$C_m \frac{dV_i^\alpha}{dt} = -g_L(V_i^\alpha - V_L) + I_{i,syn}^\alpha(t) + I_{i,app}^\alpha(t), \text{ if } V_i^\alpha < V_{th}. \quad (4.1)$$

When neurons reach the threshold  $V_{th}$ , a spike is emitted and they are reset to  $V_{rt}$  for an absolute refractory period  $\tau_{ref}$ . The spike times  $t_i^\alpha$  are recorded.

The default synapse model in SpikeNet is conductance-based. The synaptic currents received by a neuron are given by

$$I_{i,syn}^\alpha(t) = \sum_{\beta=1}^P I_i^{\alpha\beta}(t) \quad (4.2)$$

$$= \sum_{\beta=1}^P [-g_i^{\alpha\beta}(V_i^\alpha - V_{rev}^\beta)] \quad (4.3)$$

$$= \sum_{\beta=1}^P \left\{ - \left[ \sum_{j=1}^{N_\beta} a_{ij}^{\alpha\beta} g_{ij}^{\alpha\beta} s_{ij}^{\alpha\beta}(t) \right] (V_i^\alpha - V_{rev}^\beta) \right\} \quad (4.4)$$

where  $V_{rev}^\beta$  is the reversal potential of the corresponding current  $I_i^{\alpha\beta}$  induced by pre-synaptic population  $\beta$ .  $a_{ij}^{\alpha\beta}$  is a binary variable which determines the existence of synapse from the  $j$ -th neuron in population  $\beta$  to the  $i$ -th neuron in population  $\alpha$ , while  $g_{ij}^{\alpha\beta}$  reflects the (maximal) strength of the synaptic conductance. The gating variable  $s_{ij}^{\alpha\beta}(t)$  models the instantaneous value of synaptic conductance in terms of the fraction of open channels, described by

$$\frac{ds_{ij}^{\alpha\beta}}{dt} = -\frac{s_{ij}^{\alpha\beta}}{\tau_d^\beta} + \sum_{t_j^\beta} h^\beta(t - t_j^\beta - d_{ij}^{\alpha\beta})(1 - s_{ij}^{\alpha\beta}) \quad (4.5)$$

where  $h$  models the concentration time-course of the channel-opening neurotransmitters, arrived with a conduction delay  $d_{ij}^{\alpha\beta}$  after the pre-synaptic spike time  $t_j^\beta$ . The  $(1 - s_{ij}^{\alpha\beta})$  term introduces saturation effect. Following the simplification in [1], a rectangular pulse with unitary area is used for  $h$

$$h(t) = \begin{cases} 1/\tau_r, & \text{if } 0 \leq t \leq \tau_r \\ 0, & \text{otherwise} \end{cases} \quad (4.6)$$

All numerical values are in consistent units unless mentioned otherwise (ms for time, mV for voltage, nA for current, nF for capacitance and  $\mu\text{S}$  for conductance). Default numerical integration is performed using Euler method and the suggested time-step is 0.1 ms [6].

## 4.2 Currently available models

1. Exponential leaky integrate-and-fire neuron model
2. Double-exponential synapse model: see [5]
3. Inhibitory plasticity: see [9]
4. Spike frequency adaptation: see [7]

## 5 Matlab user interface

See main\_demo.m for a list of the basic case-building matlab functions and their usages. Each such function implements one particular input protocol.

```

1 function main_demo()
2 % Use coherent units (msec+mV+nF+miuS+nA) unless otherwise stated
3
4
5 %%% Seed the Matlab random number generator
6 seed = 1;
7
8 %%% Open new (uniquely time-stamped) input files for the SpikeNet C++
9 % simulator.
10 [FID] = new-ygin-files-and-randseedHDF5(seed);
11
12 %%% Define some basic parameters
13 % Time step (ms)
14 dt = 0.1; % 0.1 is usually small enough
15 % Total number of simulation steps
16 step_tot = 10^2;
17 % Create two neuron populations with 50 neurons in the 1st population
18 % and 10 neurons in the 2nd population.
19 N = [40, 10];
20 % Write the above basic parameters to the input file
21 writeBasicParaHDF5(FID, dt, step_tot, N);
22
23

```

```

24  %%% Define non-parameters for the neuorn model
25  % For demo purpose, the values used as following are the still the
26  % default ones.
27  % If default values are to be used, there is no need to re-define them.
28  Cm = 0.25; % (nF) membrane capacitance
29  tau_ref = 2.0; % (ms) absolute refractory time
30  V_rt = -60.0; % (mV) reset potential
31  V_lk = -70.0; % (mV) leaky reversal potential
32  V_th = -50.0; % (mV) firing threshold
33  g_lk = 0.0167; % (muS) leaky conductance (note that Cm/gL=15 ms)
34  for pop_ind = 1:2
35      writePopParaHDF5(FID, pop_ind, 'Cm', Cm, 'tau_ref', tau_ref, 'V_rt', V_rt, ...
36          'V_lk', V_lk, 'V_th', V_th, 'g_lk', g_lk);
37  end
38
39  %%% Add spike-frequency adaptation to the 1st population
40  pop = 1;
41  writeSpikeFreqAdptHDF5(FID, pop);
42
43
44  % % Use Adam 2016 synapse model
45  % model_choice = 2;
46  % writeSynapseModelChoiceHDF5(FID, model_choice)
47
48
49  %%% Define the initial condition
50  p_fire = [0.1 0.1]; % initial firing probabilities for both populations
51  % set initial V distribution to be [V_rt, V_rt + (V_th-V_rt)*r_V0]
52  r_V0 = [0.5 0.5];
53  writeInitCondHDF5(FID, r_V0, p_fire)
54
55  %%% Add external Poissonian spike trains into the 1st population
56  pop = 1;
57  type_ext = 1; % 1 for AMPA-like synapses
58  g_ext = 2*10^-3; % synaptic coupling strength (muS)
59  N_ext = 1000; % No. of independent external connections onto each neuron
60  rate_ext = 2*ones(1, step_tot); % Poisson rate for each time step (Hz)
61  neurons_recv = zeros(1, N(pop));
62  neurons_recv(1:10) = 1; % only neurons #1-10 receive such external input
63  writeExtSpikeSettingsHDF5(FID, pop, type_ext, g_ext, N_ext, rate_ext, ...
64      neurons_recv );
65
66
67  %%% Add external currents (Gaussian white noise) to the 2nd population
68  pop = 2;
69  I_ext_mean = 0.5*ones(1, N(2)); % defined for each neuron (nA)
70  I_ext_std = 0.2*ones(1, N(2)); % defined for each neuron (nA)
71  writeExtCurrentSettingsHDF5(FID, pop, I_ext_mean, I_ext_std)
72
73  %%% Add external conductances (Gaussian white noise) to the 2nd population
74  % The default reversal potential is V_ext = 0.0 mV.
75  pop = 2;
76  g_ext_mean = 50*10^-3*ones(1, N(2)); % defined for each neuron (muS)
77  g_ext_std = 0.0*ones(1, N(2)); % defined for each neuron (muS)
78  writeExtConductanceSettingsHDF5(FID, pop, g_ext_mean, g_ext_std)
79
80
81  %%% Define runaway killer

```

```

82 % The computational cost of the simulation is directly proportional to
83 % the average firing rate of the network. Very often, your parameters
84 % may lead to biologically unrealistically high firing rate or even
85 % runaway activity (the highest rate possible  $\sim 1/\tau_{ref}$ ). To save the
86 % computational resources for more interesting simulation cases, it is
87 % advised to define the runaway killer.
88 % Note that the simulator will still output all the relevant data before
89 % the kill.
90 min_ms = 500; % the min simulation duration that should be guaranteed
91 runaway_Hz = 40; % the threshold above which the simu should be killed
92 Hz_ms = 200; % the window length over which the firing rate is averaged
93 pop = 1; % the population to be monitored by the runaway killer
94 writeRunawayKillerHDF5(FID, pop, min_ms, runaway_Hz, Hz_ms);
95
96
97 %%% Record the basic statistics for the 1st neuron population
98 pop = 1;
99 writePopStatsRecordHDF5(FID, pop);
100
101 %%%%%%%%%%%%%%% Chemical Connections %%%%%%%%%%%%%%%
102 % type(1:AMAP, 2:GABAA, 3:NMDA)
103 % Define AMAP-like excitatory synaptic connection within the 1st pop
104 pop_pre = 1;
105 pop_post = 1;
106 syn_type = 1; % 1 for AMPA-like synapse
107 g_EE = 10*10^-3; % synaptic coupling strength (mS)
108 % random adjacency matrix with a wiring probability of 0.2
109 A = rand(N(1), N(1)) < 0.2;
110 [I_EE, J_EE] = find(A);
111 K_EE = g_EE*ones(size(I_EE)); % identical coupling strength
112 D_EE = rand(size(I_EE))*5; % uniformly random conduction delay [0, 5] ms
113 writeChemicalConnectionHDF5(FID, syn_type, pop_pre, pop_post, ...
114     I_EE, J_EE, K_EE, D_EE);
115
116 % Define AMAP-like excitatory synaptic connection from pop 1 to pop 2
117 pop_pre = 1;
118 pop_post = 2;
119 syn_type = 1; % 1 for AMPA-like synapse
120 g_IE = 10*10^-3; % synaptic coupling strength (mS)
121 % random adjacency matrix with a wiring probability of 0.5
122 A = rand(N(1), N(2)) < 0.5;
123 [I_IE, J_IE] = find(A);
124 K_IE = g_IE*ones(size(I_IE)); % identical coupling strength
125 D_IE = rand(size(I_IE))*5; % uniformly random conduction delay [0, 5] ms
126 writeChemicalConnectionHDF5(FID, syn_type, pop_pre, pop_post, ...
127     I_IE, J_IE, K_IE, D_IE);
128
129 % Define GABA-like excitatory synaptic connection from pop 2 to pop 1
130 pop_pre = 2;
131 pop_post = 1;
132 syn_type = 2; % 2 for GABA-like synapse
133 g_EI = 10*10^-3; % synaptic coupling strength (mS)
134 % random adjacency matrix with a wiring probability of 0.5
135 A = rand(N(2), N(1)) < 0.5;
136 [I_EI, J_EI] = find(A);
137 K_EI = g_EI*ones(size(I_EI)); % identical coupling strength
138 D_EI = rand(size(I_EI))*5; % uniformly random conduction delay [0, 5] ms
139 writeChemicalConnectionHDF5(FID, syn_type, pop_pre, pop_post, ...

```

```

140     I_EI, J_EI, K_EI, D_EI);
141
142 % Define GABA-like excitatory synaptic connection within pop 2
143 pop_pre = 2;
144 pop_post = 2;
145 syn_type = 2; % 2 for GABA-like synapse
146 g_II = 20*10^-3; % synaptic coupling strength (mS)
147 % random adjacency matrix with a wiring probability of 0.5
148 A = rand(N(2), N(2)) < 0.5;
149 [I_II, J_II] = find(A);
150 K_II = g_II*ones(size(I_II)); % identical coupling strength
151 D_II = rand(size(I_II))*5; % uniformly random conduction delay [0, 5] ms
152 writeChemicalConnectionHDF5(FID, syn_type, pop_pre, pop_post, ...
153     I_II, J_II, K_II, D_II);
154 %%%%%%%%%%%%%%% Chemical Connections Done %%%%%%%%%%%%%%%
155
156
157 %%% Use an existing synapse connectivity definition file instead of
158 % generating a new one:
159 % (The feature needs to be written)
160
161
162 %%% Define non-default synapse parameters
163 writeSynParaHDF5(FID, 'tau_decay_GABA', 3);
164 % "help writeSynPara" to see all the parameter names and default values
165
166 %%% Add short-term depression to the synapses with the 1st population
167 pop_pre = 1;
168 pop_post = 1;
169 step_start = round(step_tot/3); % Turn on STD at this time step
170 writeSTDHDF5(FID, pop_pre, pop_post, step_start);
171
172
173 %%% Add inhibitory STDP to the synapses from pop 2 to pop 1
174 pop_pre = 2;
175 pop_post = 1;
176 % Turn on inhibitory STDP at a certain time step
177 step_start = round(step_tot/3*2);
178 writeInhSTDPHDF5(FID, pop_pre, pop_post, step_start);
179
180 %%% Record the basic statistics for the excitatory synapses within
181 % the 1st neuron population
182 pop_pre = 1;
183 pop_post = 1;
184 syn_type = 1; % 1 for AMPA-like synapse
185 writeSynStatsRecordHDF5(FID, pop_pre, pop_post, syn_type);
186
187 %%% Sample detailed time series data from the 1st population
188 pop = 1;
189 sample_neuron = 1:10:N(1); % sample every 10th neuron
190 sample_steps = 1:2:step_tot; % sample every 2nd time step
191 sample_data_type = [1,1,1,1,0,0,1,0];
192 % The logical vector above corresponds to
193 % [V, I_leak, I_AMPA, I_GABA, I_NMDA, I_GJ, I_ext, I_K]
194 writeNeuronSamplingHDF5(FID, pop, sample_data_type, ...
195     sample_neuron, sample_steps)
196
197 %%% Optional: record explanatory variables (scalars only)

```



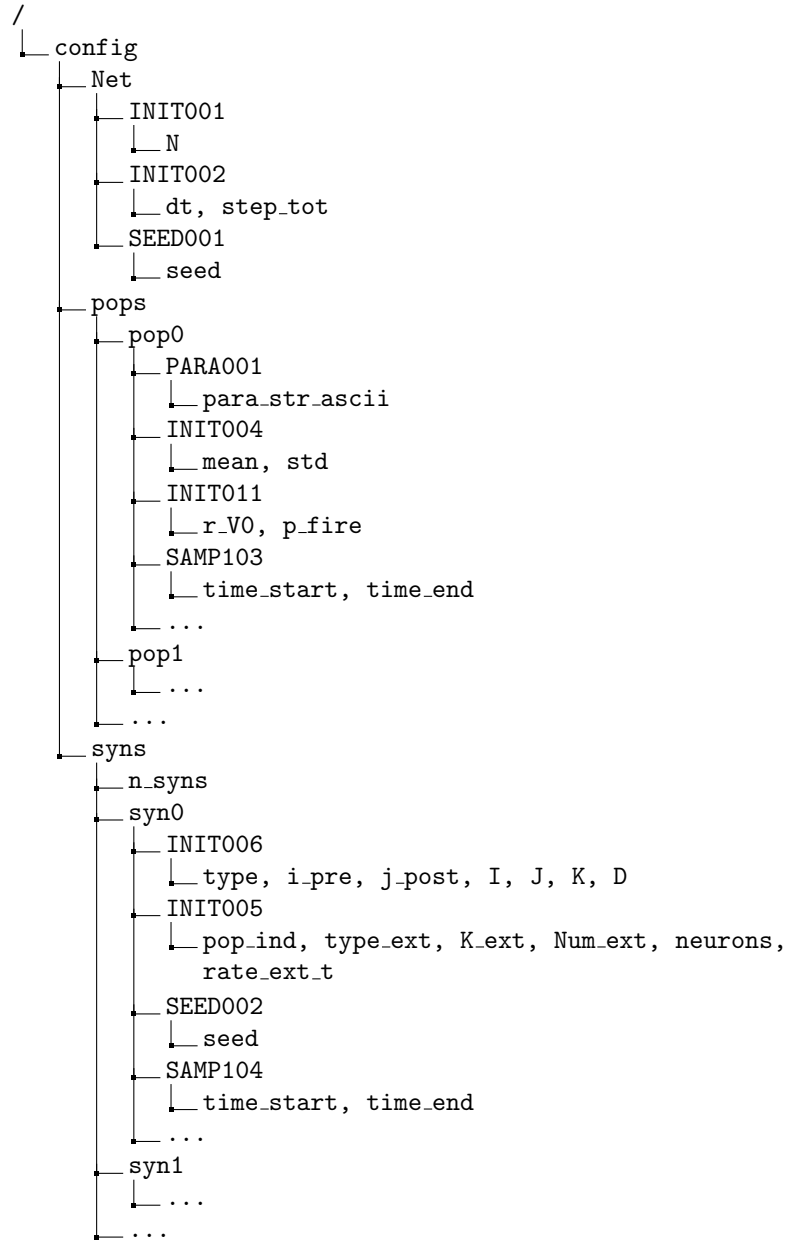
```

198 % They will also be used in pro-processsing for auto-generated comments
199 discard_transient = 0; % transient period data to be discarded (ms)
200 comment1 = 'This is a demo.';
201 comment2 = ['If you have any question regarding SpikeNet,'...
202             'please contact Yifan Gu (yigu8115@gmail.com).'];
203 writeExplVarHDF5(FID, 'discard_transient', discard_transient, ...
204                   'g_EE', g_EE, ...
205                   'g_EI', g_EI, ...
206                   'g_IE', g_IE, ...
207                   'g_II', g_II, ...
208                   'g_ext', g_ext, ...
209                   'N_ext', N_ext, ...
210                   'rate_ext', rate_ext,...
211                   'comment1', comment1, 'comment2', comment2);
212
213 %%% append this matlab file to the input file for future reference
214 appendThisMatlabFileHDF5(FID)
215
216 end
217
218
219 function appendThisMatlabFileHDF5(FID)
220
221 % need to coopy and past the following code into the file to be appended!
222 text = fileread([mfilename('fullpath'), '.m']);
223 hdf5write(FID, '/config/MATLAB/config.m', text, 'WriteMode', 'append');
224
225 end

```

(More need to be added on the available post-processing Matlab functions. SpikeNet has a variety of statistical analysis and visualization tools for spiking networks.)  
 ++Add descriptions of CollectVectorYG and CollectCellYG.

## 6 Input/Output protocols



### 6.1 Notes on RNG control

To fully control the RNG in C++ simulator, you need to pass the seed via this two functions.

1. writeExtSpikeSettingsHDF5(..., Seed)
2. writePopSeedHDF5(PopID, Seed)

## References

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- [4] Matthias H Hennig. Theoretical models of synaptic short term plasticity. *Neural Information Processing with Dynamical Synapses*, page 5, 2015.
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