

LsmTool : Analysing the Computational Power of neural microcircuits

Version 1.0

User Manual

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Contents

1	Introduction	3
1.1	What is <code>LsmTool</code> ?	3
1.2	About this manual	3
1.3	Features of the current version	3
1.4	Getting and Installing <code>LsmTool</code>	3
2	An Introductory example	4
2.1	Algorithm for offline training of the threshold gate	5
2.2	Basic Concepts	5
2.3	Implementation with <code>LsmTool</code>	6
3	Function reference	8

1 Introduction

1.1 What is LsmTool ?

LsmTool is a set of Matlab scripts that allows to assess the real-time computing capability of neural microcircuit models. LsmTool is based on a new theoretical framework for analysing real time computations in neural microcircuits: the [Liquid State Machine](#) (Sec. ??).

To get a thorough understanding of LsmTool it is a good idea to read the paper describing the basic ideas [Maass et al., 2002] as well as the paper which describes on a higher level this software package [Natschläger et al., 2002a].

1.2 About this manual

This manual is intended to describe how to use the Matlab scripts provided by LsmTool to perform computer experiments within the LSM framework.

We assume that the reader has [Matlab](#) programming knowledge.

Although a short introduction into [the basic concept of the LSM](#) (Sec. ??) is given we strongly recommend to read [Maass et al., 2002, Natschläger et al., 2002b].

This manual is also available in HTML format either online via <http://www.lsm.tugraz.at/lsmtool/usermanual> or locally at your computer as `file:<somepath>/lsm/lsmtool/documentation/usermanual/index.html` if you have installed (unzipped) LsmTool in the directory `<somepath>`.

1.3 Features of the current version

Matlab interface LsmTool is mainly written in Matlab and hence

Runs under Unix (Linux) and Windows

Object oriented design All the [Learning Algorithms](#) (Sec. ??), [target functions](#) (Sec. ??), and [readouts](#) (Sec. ??) are implemented as [Matlab classes](#).

Parallel Processing Usually the [training of a readout](#) (Sec. ??) involves many simulations of the same microcircuit with different inputs and training of several readouts. This can easily be run in parallel. LsmTool provides means to do this in a convenient way (by employing the Parallel Matlab Toolbox [Svahn, 2001]).

1.4 Getting and Installing LsmTool

LsmTool is distributed under the [GNU General Public License](#) and can be downloaded from <http://www.igi.tugraz.at/lsmtool>.

To install LsmTool perform the following steps:

1. Download LsmTool from <http://www.igi.tugraz.at/lsmtool>

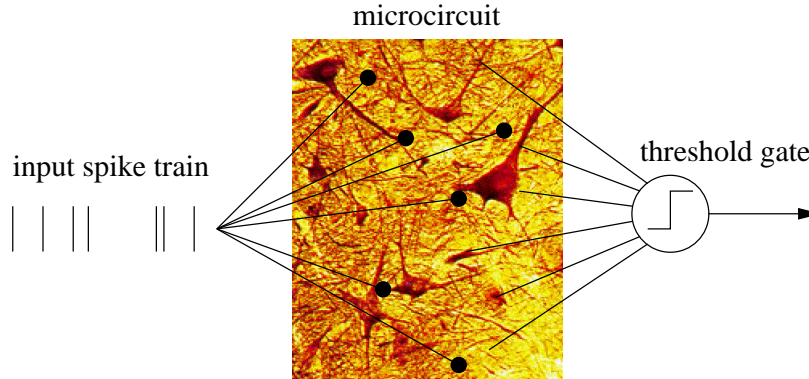


Figure 1: Architecture used to classify a spike train. The microcircuit is modeled as a network of leaky-integrate-and-fire neurons.

2. Unzip the file `lsmtool-VER.zip` where `VER` stands for the version you have downloaded.
This will create a subdirectory `lsm` and `lsm/lsmtool`
3. Start Matlab and change into the directory `lsm`
4. Run the Matlab script `install.m`.
5. Add the path `lsm` to the Matlab search path; e. g.
 - `addpath('/home/jack/lsm')}` or
 - `addpath('C:\Work\Neuroscience\lsm')`.
6. Change into the directory `lsm/lsmtool/demos` and play around with them. Have fun using `LsmTool` !

2 An Introductory example

In this section we will introduce `LsmTool` by means of an introductory example. In this simple example we will train a readout neuron modeled as a threshold gate (see [Hertz et al., 1991]) to classify a spike train. This readout neuron will receive its input from a neural microcircuit modeled as a network of leaky-integrate-and-fire neurons (see [Gerstner and Kistler, 2002]) which is stimulated by the input spike train (which should be classified). The setup is shown in Figure 1.

2.0.1 Precise definition of the classification task

Two Poisson spike trains (frequency 20 Hz, length 0.5 sec) are generated, and fixed as templates 0 and 1. The actual input spike train is generated as jittered versions of a template by varying each spike by a random drawn amount (Gaussian distribution with zero mean and a given STD; this STD is called jitter (default jitter=4 ms)). The task of the threshold gate is to output the number (0 or 1) of the (random chosen) template from which the input spike train was generated.

2.1 Algorithm for offline training of the threshold gate

Here we just outline the main body of the procedure which we will use to train the readout. This will be discussed in more detail in [Section ??](#).

1. Define the neural microcircuit to be analyzed
2. Record *spike responses* of the *neural microcircuit* caused by different *training inputs* drawn from an appropriate *input distribution*.
3. Convert the spike responses into *states* $x(t_k)$ at various *sample time points* t_k by some low-pass filtering to get a somewhat smoothed signal. This mimics the effect of spike transmission through a synapse to its postsynaptic neuron. This transformation can also be dropped if one can cope directly with the spike response.
4. Apply a *supervised learning algorithm* to a set of training examples of the form $\langle \text{state } x, \text{target-value } y \rangle$ to train a *readout function* f (a threshold gate in the case of this example) such that the actual outputs $f(x)$ are as close as possible to the target values y given by the *target function*.
5. Evaluate the performance of the trained readout (i.e. the threshold gate) on an independent *set of test inputs* (which are usually drawn from the same distribution as the training inputs).

2.2 Basic Concepts

The above description of the [basic algorithm](#) (Sec. 2.1) implicitly introduced all the basic concepts we need to know to understand how `LsmTool` works:

Input Distribution The distribution from which the training (and test) inputs are drawn. In our example the input distributio is defined byt the following simple procedure (for fixed templates 0 and 1):

1. Randomly choose template 0 or 1
2. Add noise (jitter) to each spike in the template

Neural Microcircuit The circuit which receives the input and whos response is recorded and analysed (in our example this a network of 135 leaky-integrate-and-fire neurons).

Response of the Microcircuit The response (output) of the neural microcircuit (in our example the 135 spike trains produced by the microcircuit model).

State of the Microcircuit The transformed (smoothed) response (output) of the neural microcircuit (in this examples this corresponds to a low-pass filtered (30 ms) version of the spike trains). This transformation can also be dropped if one can cope directly with the spike response.

Sample Time Points Since we can only handle finite sets of training examples we must define time points at which we want to sample the state of the microcircuit (in this example we will sample the states every 25 ms).

Readout Function A parameterized function/device which gets as input the circuit states (or in some cases directly the circuit response) and computes the outputs of the system (in this example a threshold gate).

Target Function/Filter A function which defines for each input time series the target output time series of a readout function. In mathematical terms this should be a target filter since we are talking about computations on time series.

Supervised Learning Algorithm By means of such algorithm the parameters of the readout — and only the readout — are adjusted such that the actual output of the readout matches as close as possible the target output.

Training Set Set of inputs used to determine the parameter of the readout.

Test Set Set of inputs different to the training set which is used to assess the performance of the trained readout.

As we will see each of these terms has its corresponding element within `LsmTool`.

2.3 Implementation with `LsmTool`

The full Matlab code is contained in `lsm/lsmtool/demos/spike_train_classification/spike_class.m`.

Defining the input distribution

Several input distributions are readily implemented as Matlab objects. The class `jittered_templates` (Sec. ??) provides the kind of input we need for our task. The following code line generates a `jittered_templates` object which produces single spike trains from 2 patterns with a jitter of 4 ms:

```
InputDist = jittered_templates('nChannels',1,'nTemplates',2,...
                              'Tstim',0.5,'jitter',4e-3);
```

Creating the neural microcircuit model

The following code generates a sparsely connected network of leaky-integrate-and-fire neurons. The details of the network creation are the topic of the [NmcTool User Manual](#) and thus not described here.

```
% init the model
nmc = neural_microcircuit;

% add a pool of 135 leaky-integrate-and-fire neurons
[nmc,p1] = add(nmc,'Pool','origin',[1 1 1],'size',[3 3 15]);
[nmc,pin] = add(nmc,'Pool','origin',[0 0 0],'size',[1 1 1],...
               'type','SpikingInputNeuron','frac_EXC',1);
```

```

% connect the input to the pools/pools
nmc = add(nmc,'Conn','dest',p1,'src',pin,'Cscale',0.9,...
          'type','StaticSpikingSynapse','rescale',0,'Wscale',0.15,'lambda',Inf);

% add recurrent connections within the pools
nmc = add(nmc,'Conn','dest',p1,'src',p1,'lambda',2);

% define the responses (i.e. what to record)
nmc = record(nmc,'Pool',p1,'Field','spikes');

```

Creating the Training and Test inputs

Since we have defined the circuit model and the input distribution we can now simulate the circuit with inputs drawn from this distribution and collect a training and test set. After the simulations the spike responses are lowpass filtered and the states are sampled every 25 ms.

```

% collect stimulus/response pairs for training
[train_response,train_stimuli] = collect_sr_data(nmc,InputDist,500);

% apply low-pass filter to spikes
train_states = response2states(train_response,[],[0:0.025:Tmax]);

% collect stimulus/response pairs for testing
[test_response,test_stimuli] = collect_sr_data(nmc,InputDist,200);

% apply low-pass filter to spikes
test_states = response2states(test_response,[],[0:0.025:Tmax]);

```

Setting up to train the threshold gate

Everything which has to do with the training of a readout is encapsulated in the class [external_readout](#) (Sec. ??). This object allows you to specify the target function (target filter) and the training algorithm (and several options for preprocessing). In our example we use pseudo inverse method (implemented in the class [linear_classification](#) (Sec. ??)) to determine the parameters of the threshold gate. The target function which outputs 0 (1) for all sample times (see [definition of the task](#) (Sec. 2)) is implemented in the class [segment_classification](#) (Sec. ??). Hence the code for setting up to train the threshold gate is rather short:

```

readout{1} = external_readout(...
    'description','with linear classification',...
    'targetFunction',segment_classification,...
    'algorithm',linear_classification);

```

Do the training of the threshold gate

After everything is set up properly we just need to start the training. Note that in the code below the function `function train_readouts` (Sec. ??) also measures the performance on the test set.

```
[trained_readouts, perf_train, perf_test] = train_readouts(...  
    readout,...  
    train_states,train_stimuli,...  
    test_states,test_stimuli);
```

Evaluation of the performance

After training we want to see how the network performs on individual test inputs:

```
plot_readouts(trained_readouts,test_states,test_stimuli);
```

3 Function reference

References

- [Gerstner and Kistler, 2002] Gerstner, W. and Kistler, W. (2002). *Spiking Neuron Models*. Cambridge University Press. See also <http://diwww.epfl.ch/~gerstner/BUCH.html>. 2
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- [Svahn, 2001] Svahn, E. (2001). Parallel matlab toolbox: User documentation. Master's thesis, Chalmers University of Technology, Sweden. To get a copy of the toolbox contact E. Svahn (email: ersva@igb.polymtl.ca, d96svahn@dtek.chalmers.se) or get it via <ftp://ftp-at.e-technik.uni-rostock.de/pub/pm/>. 1.3