Liquid State Machine for TI46 Dataset

EE746 - Neuromorphic Engineering Project

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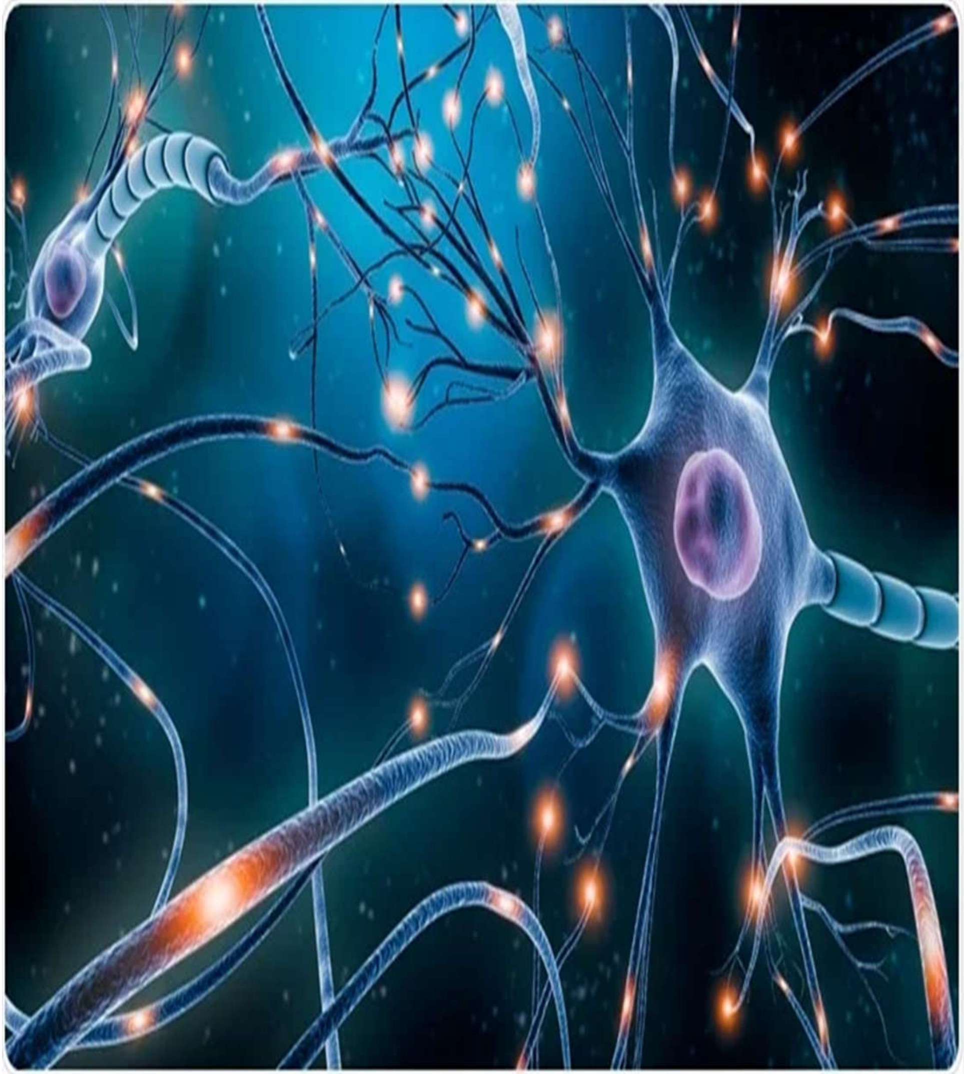
CODE Base : https://github.com/AnDa-creator/EE746-NeuromorphicEngineering



Outline

Overview of the System

Preprocessing

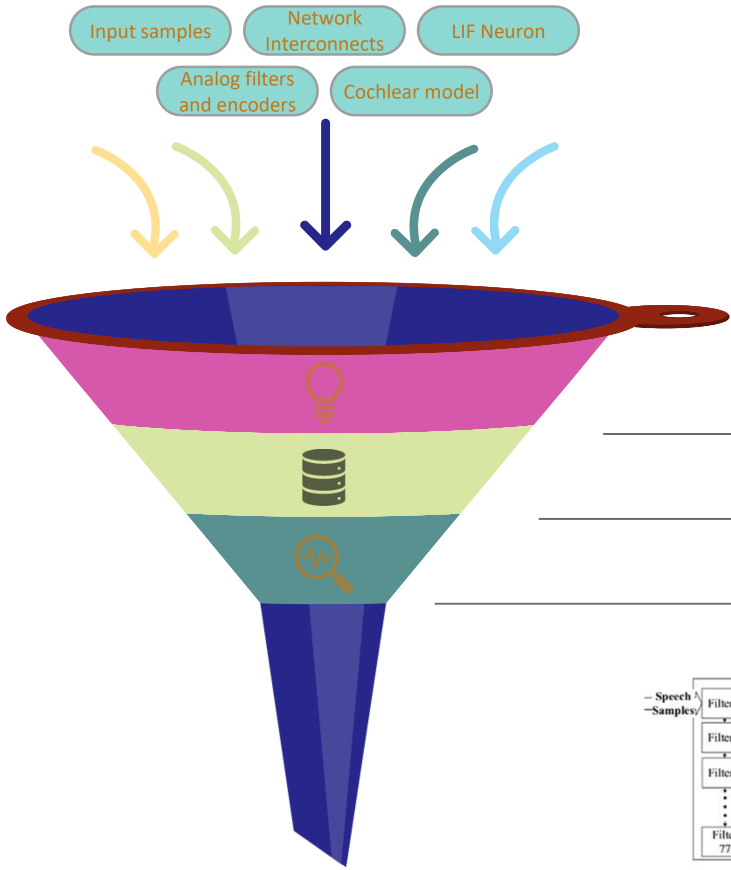
The preprocessed input is given as input to the input neurons.

Reservoir

The input neurons are connected to the neurons in reservoir via synapses.

Classifier

The Readout layer is also connected to the reservoir via plastic synapses whose weights are learned during training.



Overall System

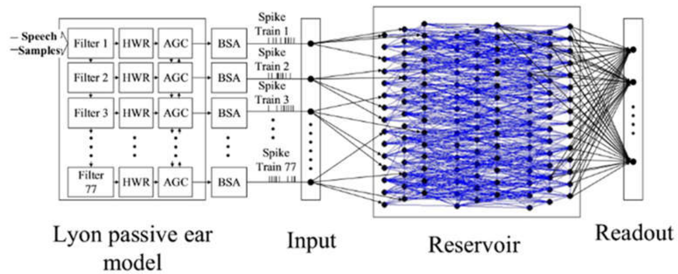
The LSM is implemented as an overall ensemble of three procedures.

TI-46 wav samples

Input spike trains

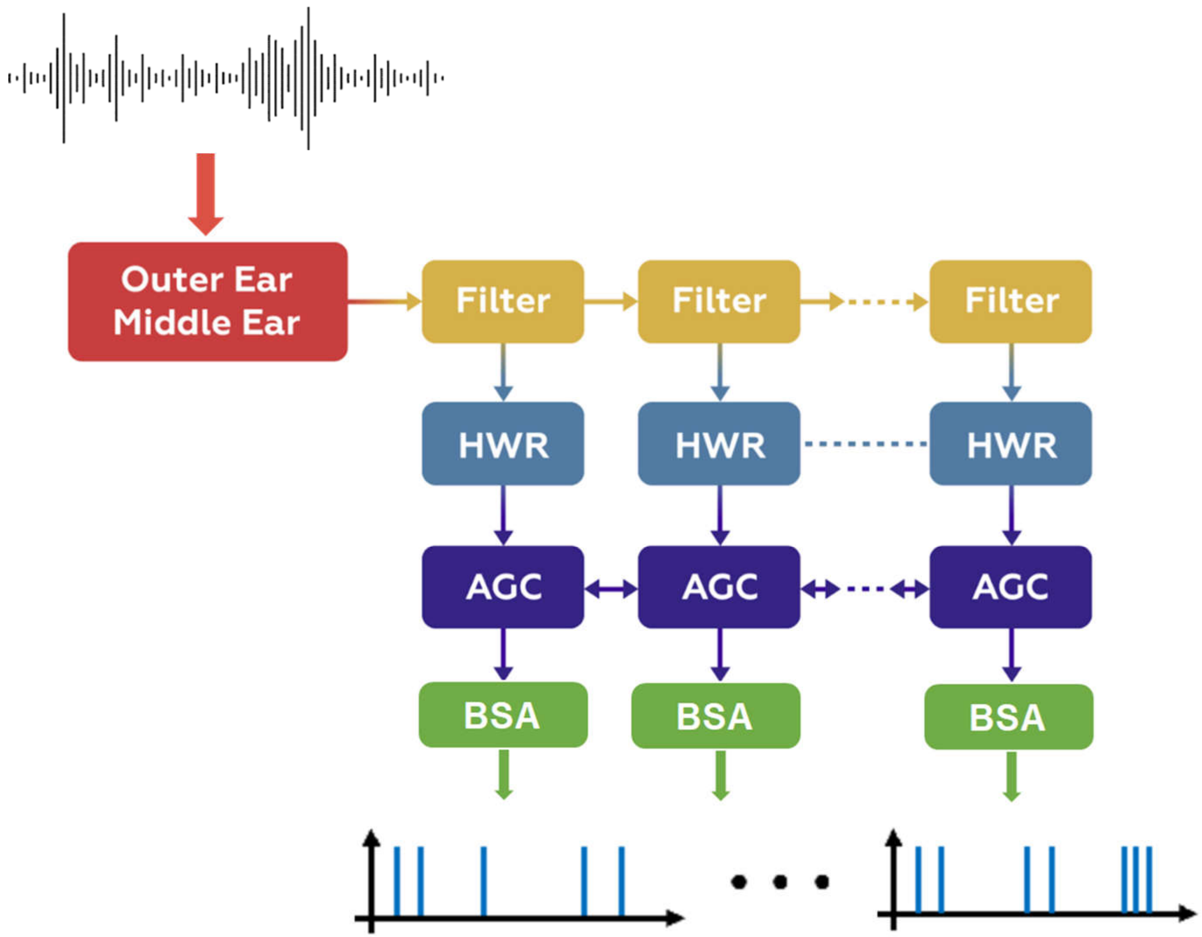
Reservoir spike data

Classifier Output



Preprocessing

- TI-46 input as Audio waveforms
- Lyon's Passive Ear Model
- Ben's Spiker Algorithm (BSA)
- Each sample gives 78 spike trains (channels)



Micromodels used in simulations

LIF Neuron

Used for Readout and reservoir neurons

$$\frac{dv_m}{dt} = -\frac{v_m}{\tau_m} + \sum_i \sum_i w_{mi} \cdot s(t - t_{ij} - d_i) + i_t(c)$$

Synapses

Three model used were →

$$\frac{dv_m}{dt} = -\frac{v_m}{\tau_m} + \sum_i \sum_j w_{mi} \cdot \delta(t - t_{ij} - d_{ij})$$

$$\frac{dv_m}{dt} = -\frac{v_m}{\tau_m} + \sum_{i,j} w_{mi} \cdot \frac{1}{\tau^s} e^{-\frac{t - t_{ij} - d_{ij}}{\tau^s}} \cdot H(t - t_{ij} - d_{ij})$$

And also 2nd order ...

Calcium dynamics

The dynamics of calcium concentration c is

$$\frac{dc}{dt} = -\frac{c}{\tau_c} + \sum_i \delta(t - t_i)$$

Learning rule(STDP)

Weight increment :

$$\begin{cases} C_\theta < C^{n-1} < C_\theta + \Delta C \\ W^{n-1} < W_{\max} \end{cases}$$

Weight decrement :

$$\begin{cases} C_\theta - \Delta C < C^{n-1} < C_\theta \\ W^{n-1} > W_{\min} \end{cases}$$

BSA encoder

$$h_{BSA} = \left(e^{-\frac{t}{\tau_{b1}}} - e^{-\frac{t}{\tau_{b2}}}\right) H(t)$$

Analog signal converted to spike train using BSA

Teacher current

The teacher current expressions used were as follows:

$$I_{\text{teach}} = \begin{cases} +I_\infty \cdot H((c_\theta + \delta c) - c), & \text{if desired} \\ -I_\infty \cdot H(c - (c_\theta - \delta c)), & \text{if undesired} \end{cases}$$

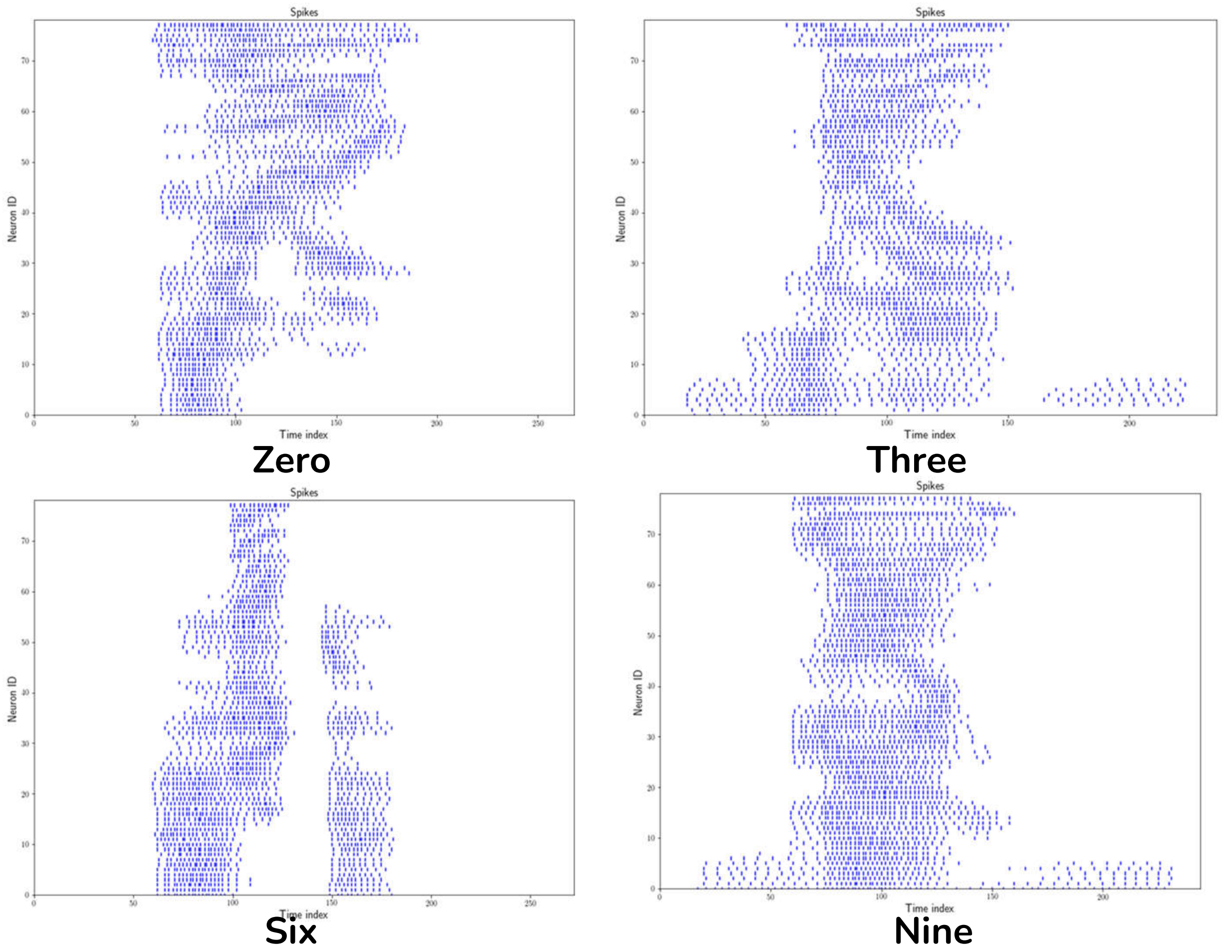
Input Neurons

The preprocessed input is a spike train, which is taken as the spikes in the input layer.

Total 78 neurons are taken in the input layer.

Each neuron is connected to 4 neurons in the next layer (Reservoir).

Weight of each synapse is 8, and each synapse is excitatory or inhibitory with probability of 0.5 .



Input Raster for various classes

Reservoir Structure

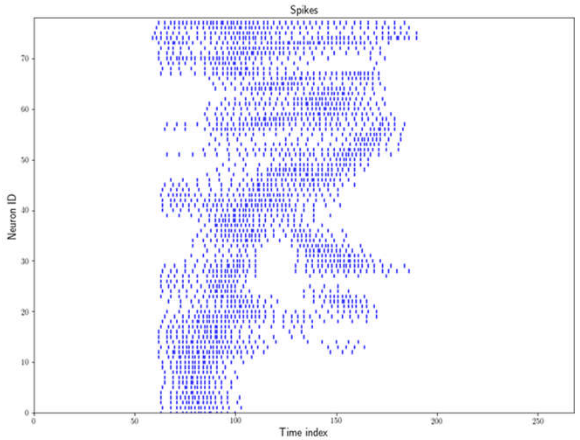
The shape of the reservoir is taken as 5x5x5.

The connection probability between 2 neurons N1,N2 is given by:

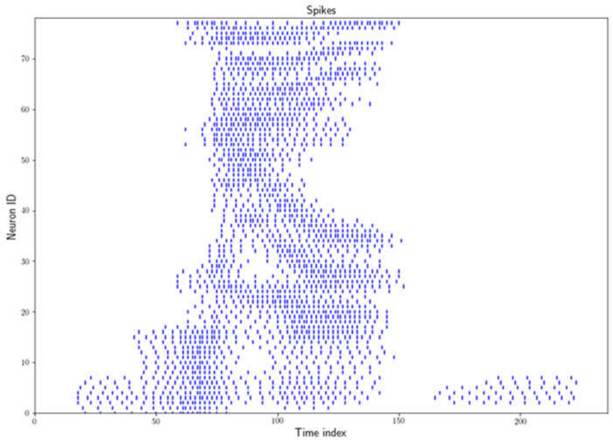
$$P_{\text{connection}}(N_1, N_2) = k \cdot e^{-\frac{D^2(N_1,N_2)}{r^2}}$$

80% neurons are taken as excitatory, 20% inhibitory.

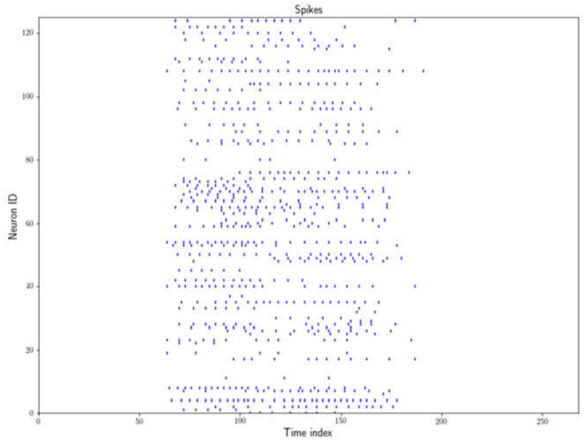
The synapses can be static, first-order or second order.



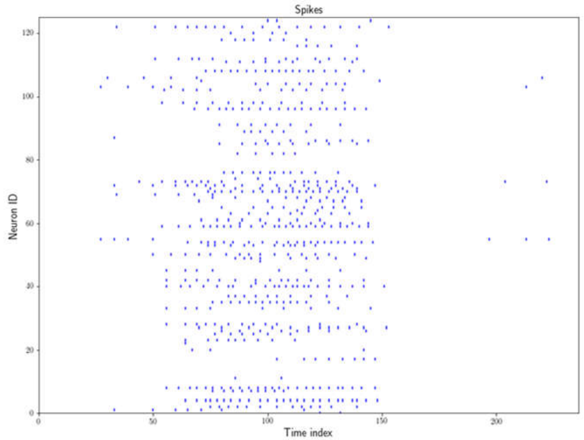
Zero



Three



Response to Zero



Response to Three

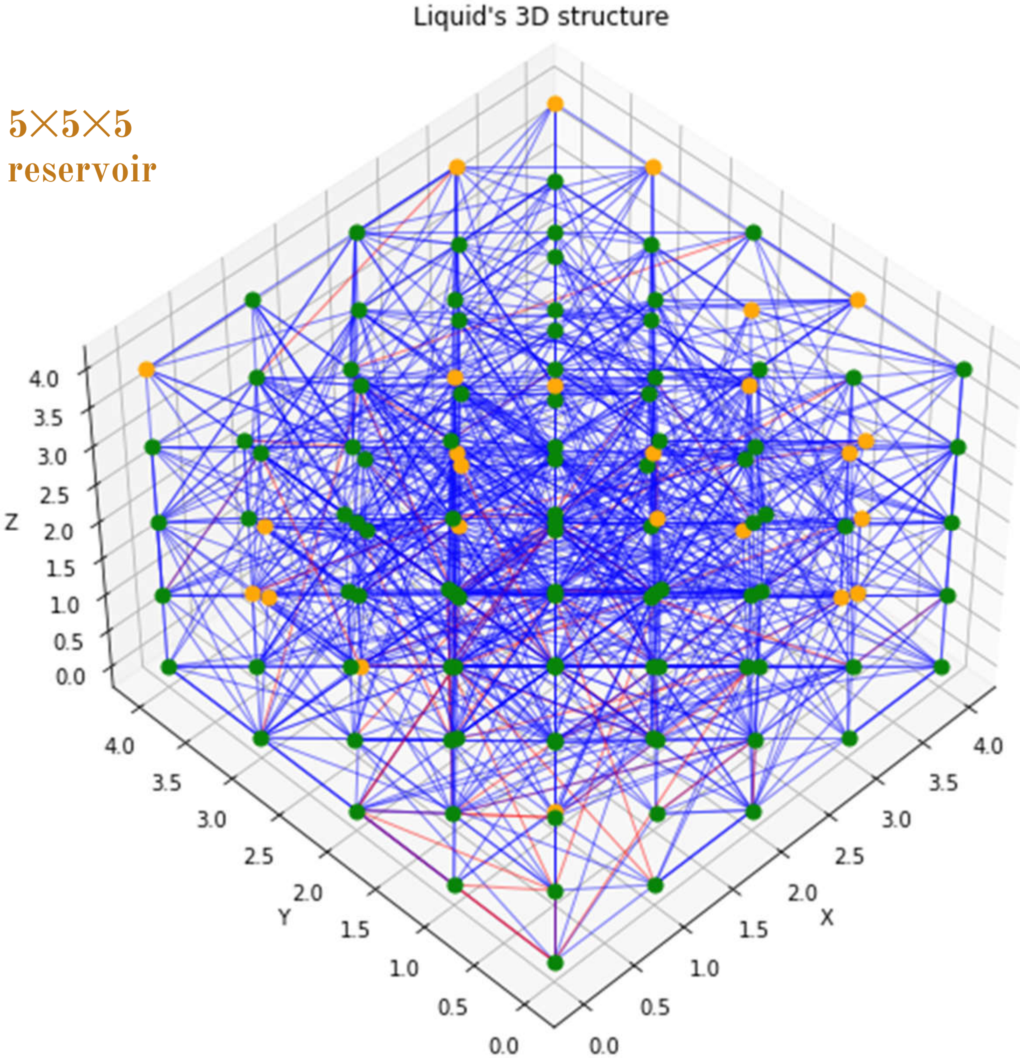
Reservoir responses for various sample inputs

Reservoir Visualization

Excitatory neuron
Inhibitory neuron
Excitatory synapse
Inhibitory synapse

Total number of synapses in the reservoir 1130
Connection-wise:
Excitatory→excitatory:769 (Weight = 3)
Excitatory→inhibitory:105 (Weight = 6)
Inhibitory→Inhibitory/Excitatory:256 (Weight = -2)

5×5×5 reservoir

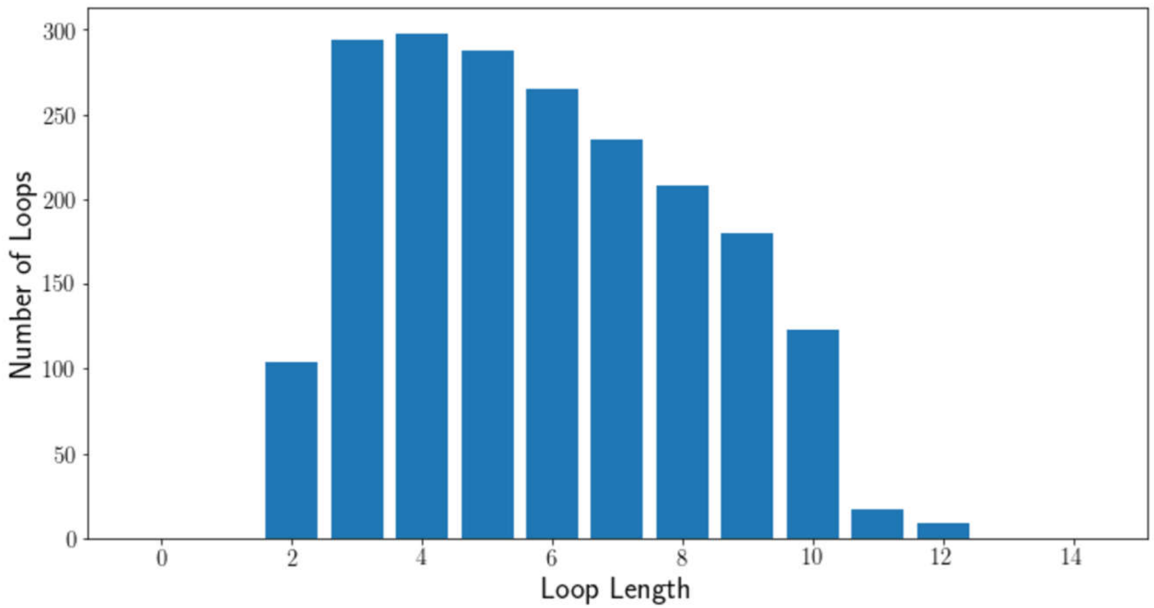


Loops Visualization

Number of loops for a given loop length (number of nodes in a loop)

This is loosely related to the time duration for which delayed coincidence may affect output

5×5×5 reservoir

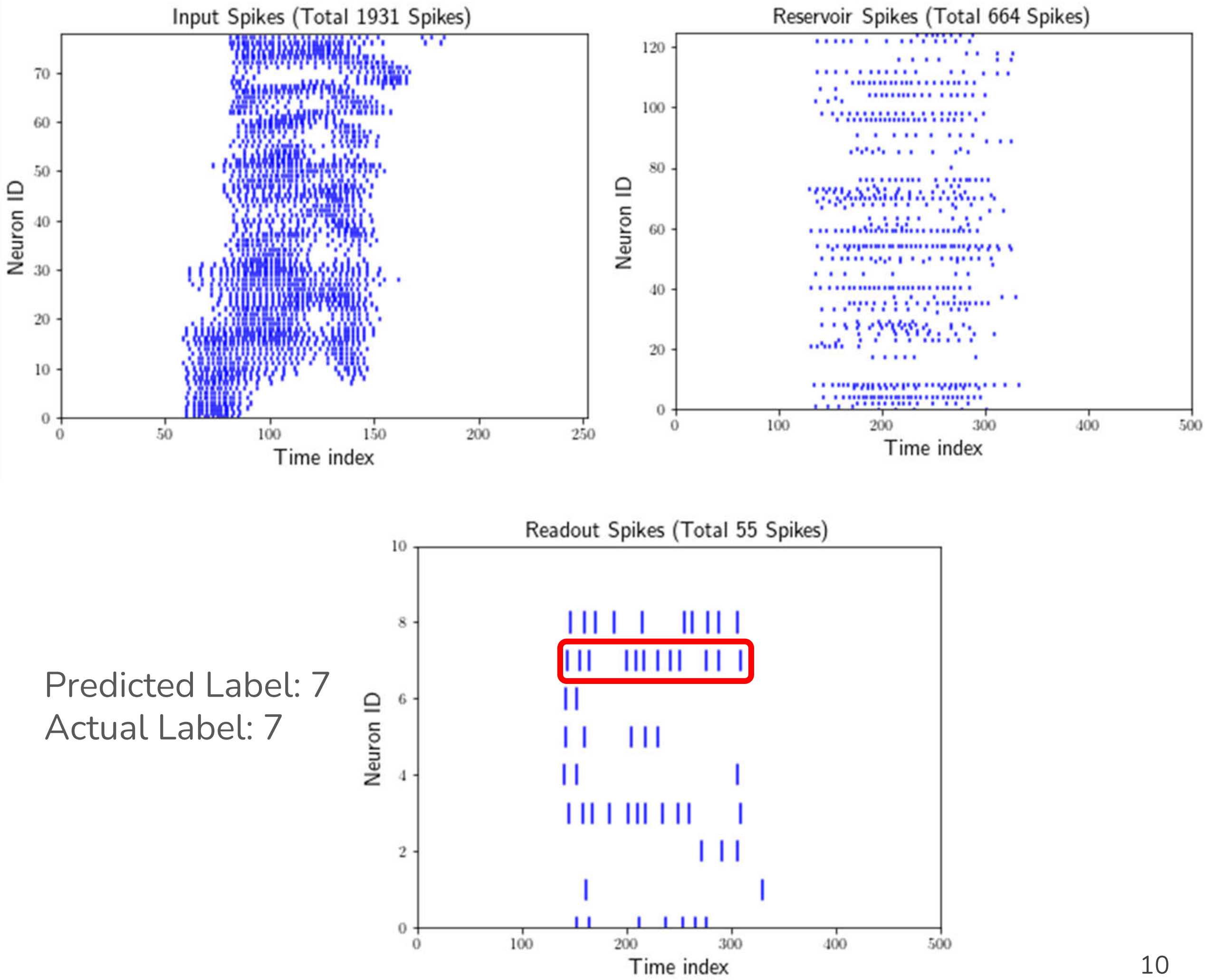


Readout Neurons

Each readout neuron is connected to all the neurons in the reservoir.

Total 10 readout neurons are considered, corresponding to 0 - 9 digits.

The class of a given input is decided by the readout neuron with most spikes.



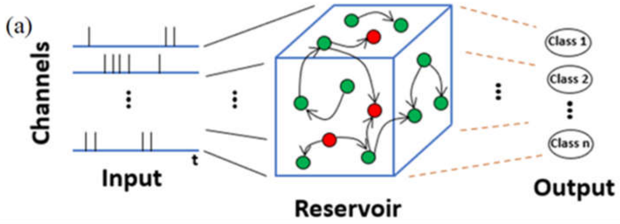
Predicted Label: 7
Actual Label: 7

Bio Inspired Learning

There are 10 output neurons(1 for each class) and the one with higher no.of spikes is chosen as the class for given input. Each readout neuron is connected to all the reservoir neurons by plastic synapses.

During training we teach the neuron with high current values so as to trigger weight changes for certain synapses tailored to a particular input. The decision of changing weights is based upon the variation of calcium concentration in the readout neurons.

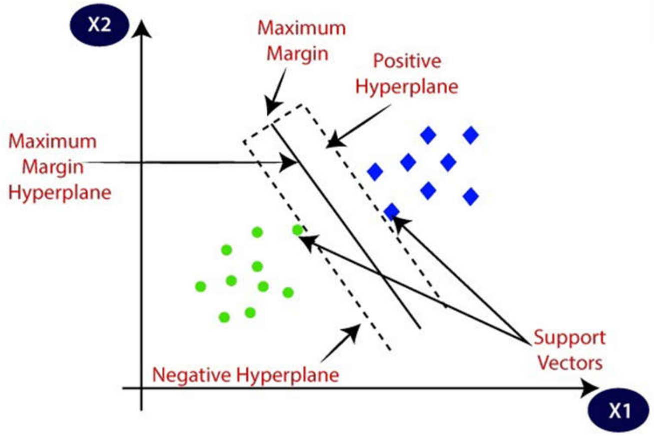
The range of the weights is taken to be -8 to 8, with a step size of 0.001. Weight update happens with a probability of 0.1.



SVM Classification

Instead of the Readout layer, the total number of spikes in each neuron of the reservoir can be taken as the input and given to an SVM classifier with linear kernel.

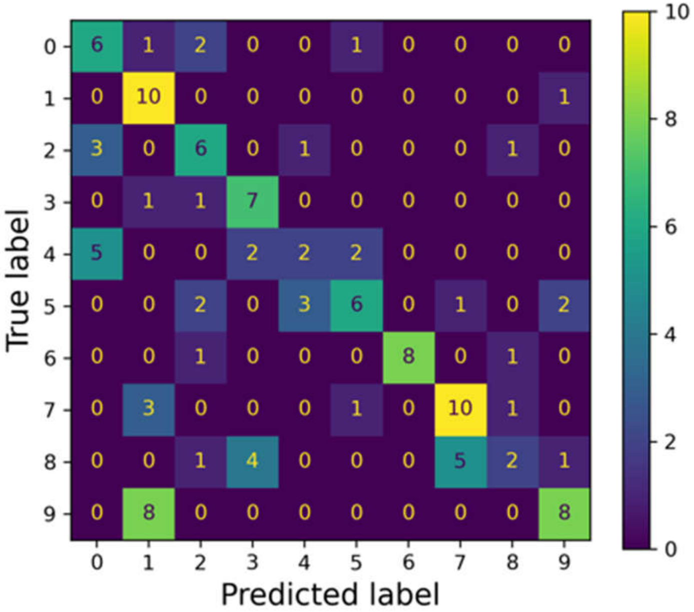
This can be done for all the 3 types of synapses.

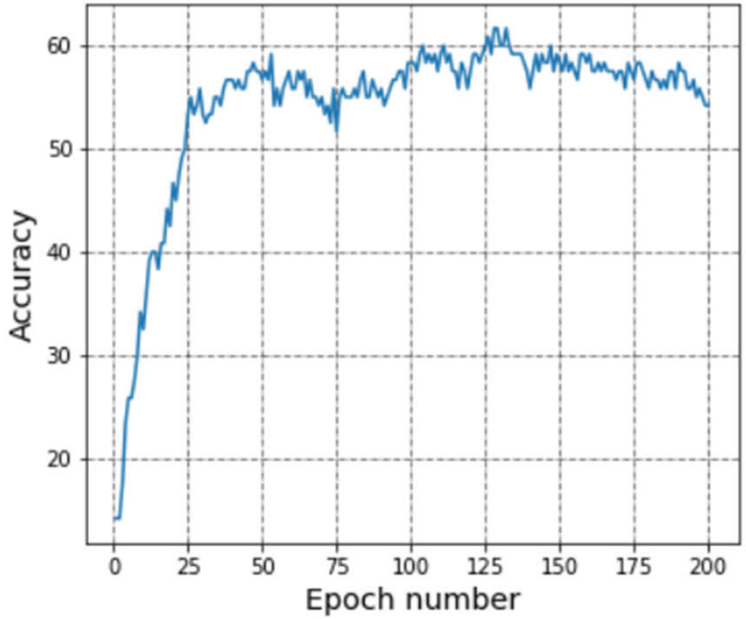


Results

Using Static synapses

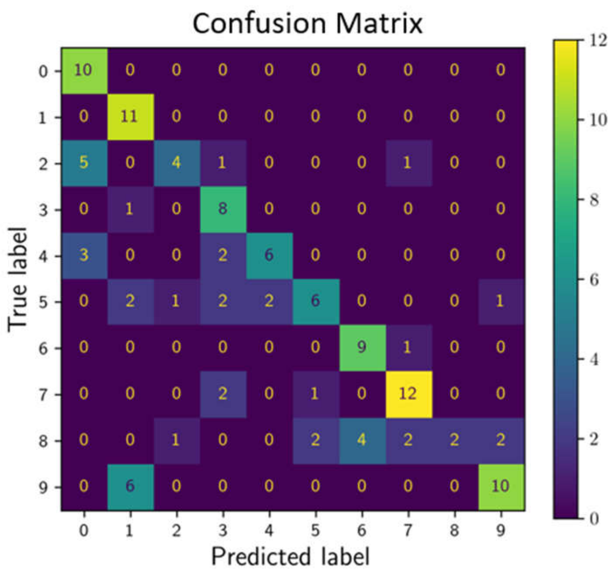
Maximum Accuracy obtained is 61.67%.

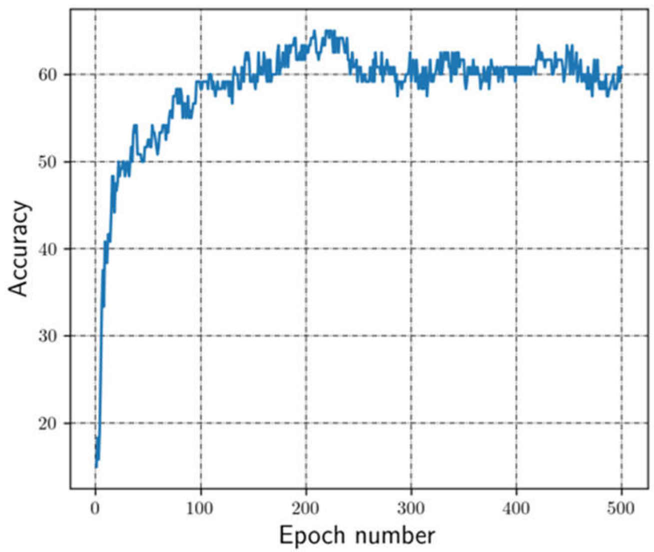




Using First-Order synapses

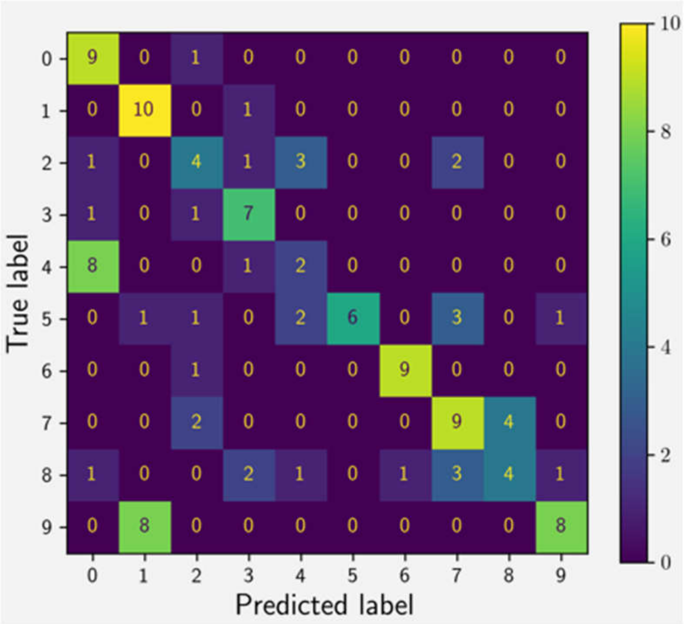
Maximum Accuracy obtained is 65%.

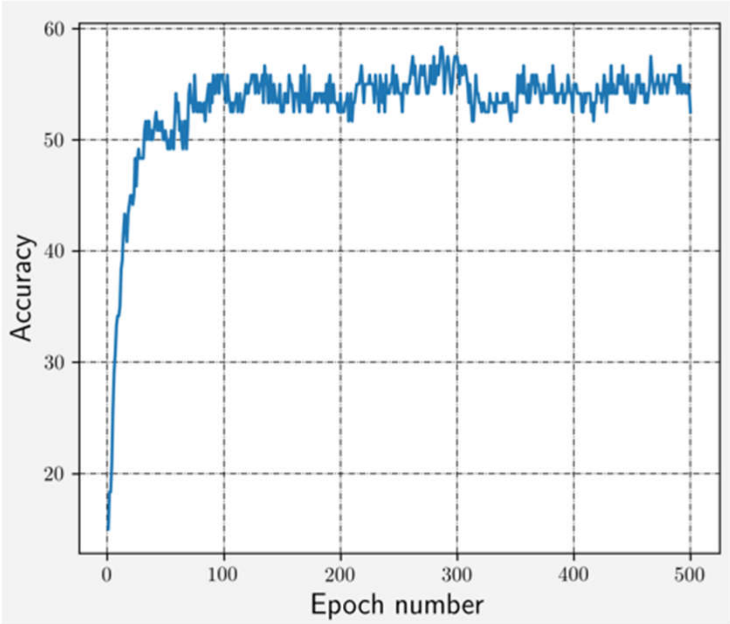




Using Second-Order synapses

Maximum accuracy obtained was 58.33 %





Conclusion

- We were not able to obtain high accuracies as mentioned in the references.
- The accuracies obtained however remained consistent after reaching the points very early, nature wise they were similar to the curves illustrated in papers.

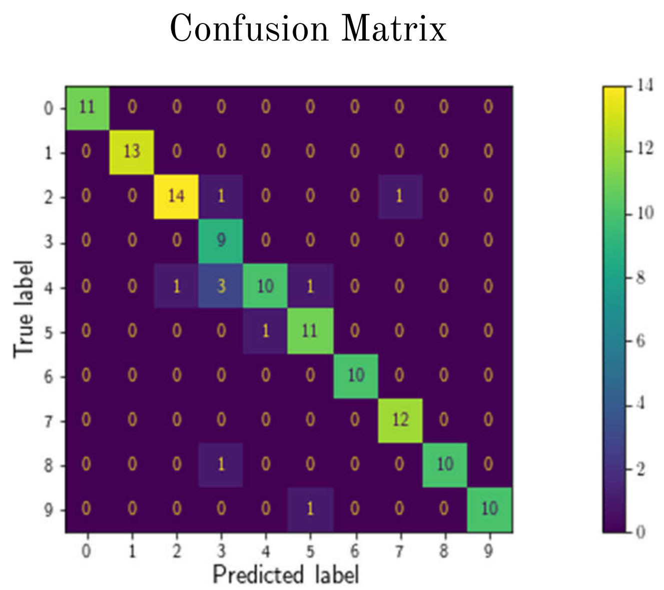
Using SVM Classifier

SVM classification with static synapses

Total number of spikes in each neuron of the reservoir is taken as the input.

SVM with linear kernel is used for classification.

Accuracy obtained is 91.67%.

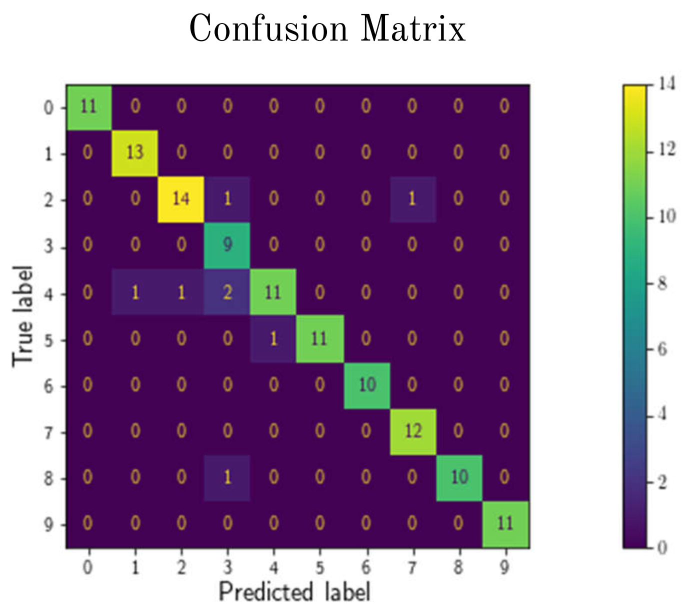


SVM classification with first-order synapses

Total number of spikes in each neuron of the reservoir is taken as the input.

SVM with linear kernel is used for classification.

Accuracy obtained is 93.33%.

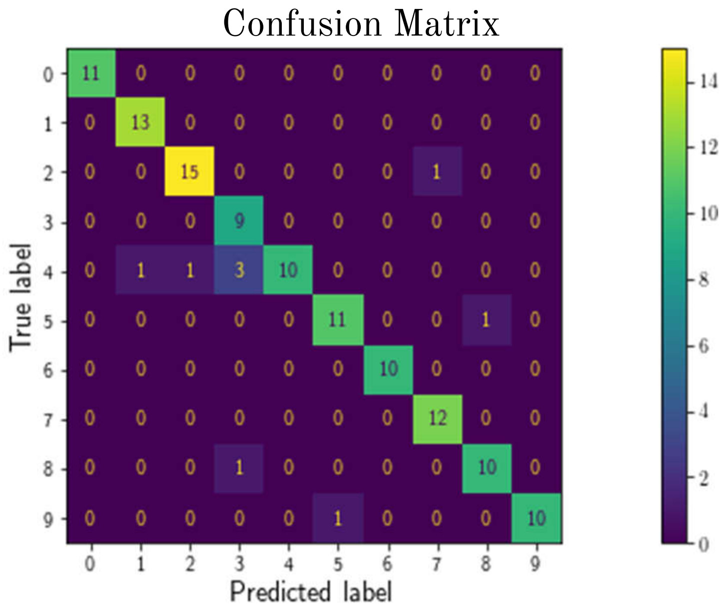


SVM classification with second-order synapses

Total number of spikes in each neuron of the reservoir is taken as the input.

SVM with linear kernel is used for classification.

Accuracy obtained is 92.5%.

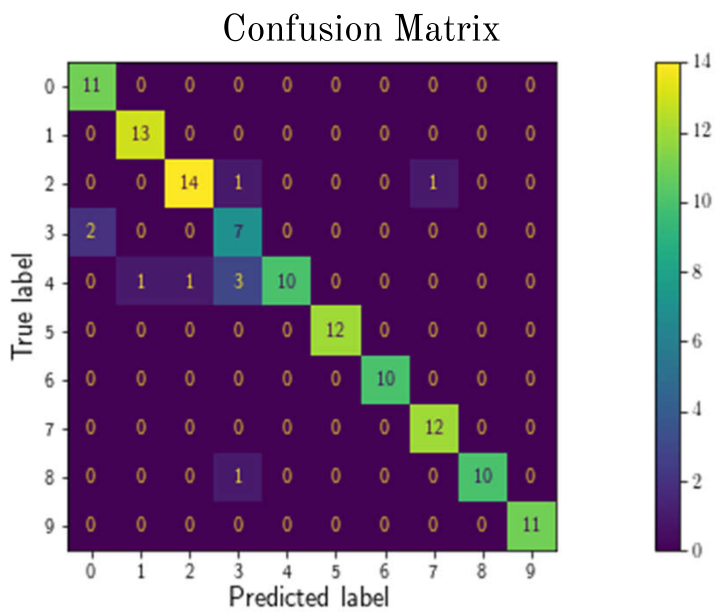


SVM classification on Input spike train

Total number of spikes in each input neuron is taken as the input.

SVM with linear kernel is used for classification.

Accuracy obtained is 91.67%.



Conclusion

- Using SVM Classifier on the output of reservoir provide increase of about 4-10% in accuracy as compared to SVM classification on input spike train.
- SVM method shows high separability and performance for our choice of parameters

References

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[2] A. Gorad, V. Saraswat and U. Ganguly, 2019 International Joint Conference on Neural Networks (IJCNN), 2019, pp. 1-8

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[4] B. Schrauwen and J. Van Campenhout, Proceedings of the International Joint Conference on Neural Networks, 2003., 2003, pp. 2825-2830 vol.4.

[5] Y. Jin and P. Li, Neurocomputing (226 l45-160), 2017