IMAGE PROCESSING WITH SPIKING NEURON NETWORKS

INTRODUCTION

- Spiking Neuron Networks (SNNs) are often referred to as the third generation of neural networks which have potential to solve problems related to biological stimuli. They derive their strength and interest from an accurate modeling of synaptic interactions between neurons, taking into account the time of spike emission.
- A spiking neural network is used to cluster images, segment images and detect edges with Hebbian based winner-take-all learning.
- It is proved that the neurons that convey information by individual spike times are computationally more powerful than the neurons with sigmoidal activation functions.

- The network architecture consists in a feedforward network of spiking neurons with multiple delayed synaptic terminals. The neurons in the network generate action potentials, or spikes, when the internal neuron state variable, called ”membrane potential”, crosses a threshold ϑ. The relationship between input spikes and the internal state variable is described by the Spike Response Model(SRM).

- Formally, a neuron j, having a set Γj of immediate predecessors (pre-synaptic neurons), receives a set of spikes with firing timesti, i ∈ Γj. Any neuron generates at most one spike during the simulation interval, and fires when the internal state variable reaches a threshold ϑ. The dynamics of the internal state variable Xj(t) are determined by the impinging spikes, whose impact is described by the spike-response function ε(t) modeling a simple α-function weighted by the synaptic efficacy Wij:

$$x_j(t) = \sum_{i \in \Gamma_j} \sum_{k=1}^{m} w_{ij}^k \varepsilon(t - t_i - d^k)$$

- The height of the post-synaptic potential (PSP) is modulated by the synaptic weight wi j to obtain the effective post-synaptic potential (PSP). ε(t) a spike-response function shaping a PSP and τ models the membrane potential decay time constant that determines the rise and decay time of the PSP. Figure 2 illustrates and equation (2) represents one of the most popular mathematical spike response models.
- We describe a presynaptic spike at a synaptic terminal k as a PSP of standard height with delay dk. The unweighted contribution of a single synaptic terminal to the state variable is then given by:

$$y_i^k(t) = \varepsilon(t - t_i - d^k)$$

- Extending equation Eq.1 to include multiple synapses per connection and inserting equation (Eq.3), the state variable xj of neuron j receiving input from all neurons i can then be described as the weighted sum of the pre-synaptic contributions:

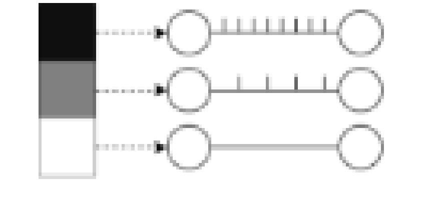
$$x_j(t) = \sum_{i \in \Gamma_j} \sum_{k=1}^{m} w_{ij}^k y_i^k(t)$$

- Where wk i j denotes the weight associated with synaptic terminal k. The firing time tj of neuron j is determined as the first time when the state variable crosses the threshold ϑ: xj(t) ≥ ϑ. Thus, the firing time tj is a non-linear function of the state variable xj : tj = tj(xj).

NEURAL CODING SCHEMES

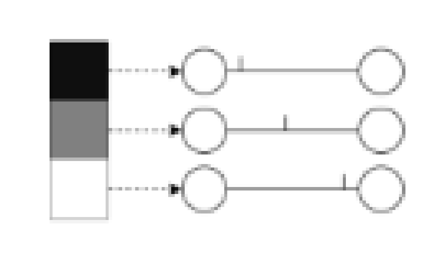
- Rate Coding

  The neurons corresponding to inputs with the highest intensities fire more frequently.



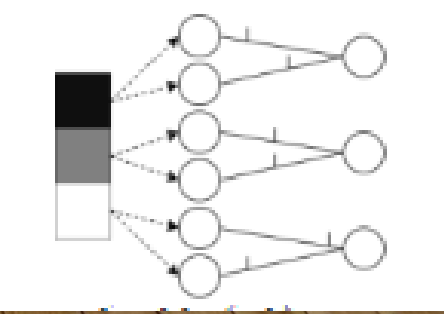
- Temporal coding

  The neurons corresponding to inputs with the highest intensities spike first.



- Population coding

  The spike times of several input neurons are used to represent the input data



NEURAL MODELS FOR SNNS

- **Integrate and fire (IF) Model**

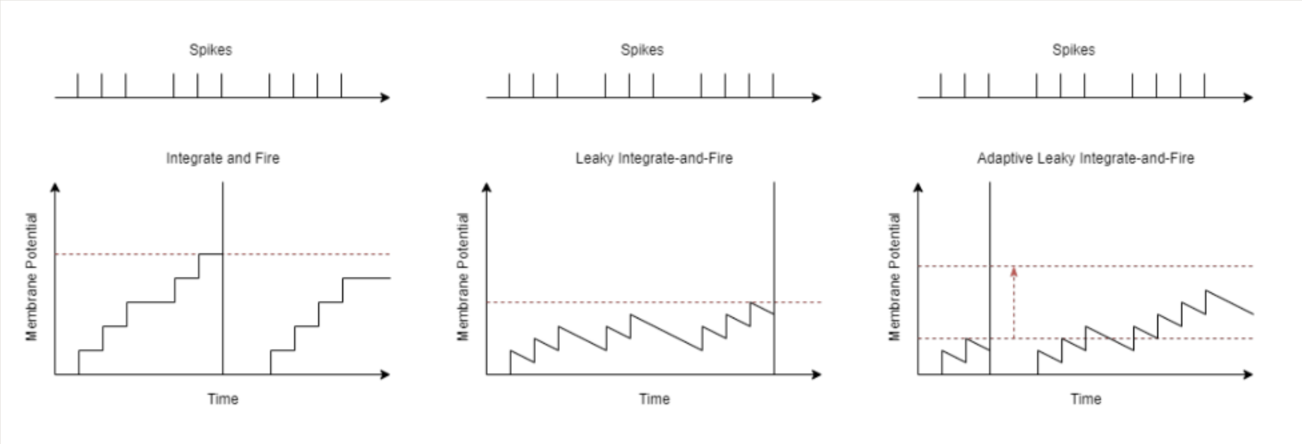
  The membrane potential increments until it reaches a specified threshold

- **Leaky Integrate and Fire (LIF) Model**

  Like the IF model except the membrane potential decrements towards a resting value.

- **Adaptive LIF Model**

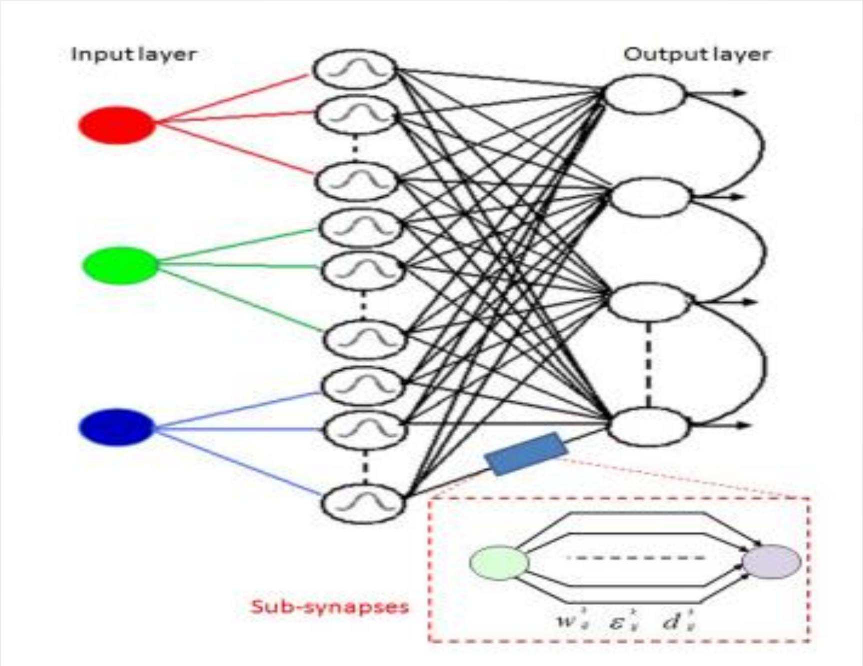
  Like the LIF model except the threshold value increments each time the neuron fires.


Spikes
Integrate and Fire
Membrane Potential
Time
Spikes
Leaky Integrate-and-Fire
Membrane Potential
Time
Spikes
Adaptive Leaky Integrate-and-Fire
Membrane Potential
Time

SNN ARCHITECTURE FOR CLUSTERING IMAGES

- The network consists in an input layer, a hidden layer, and an output layer
- The first layer is composed of three inputs neurons (RGB values) of pixels.
- It has a localized activation $\phi n = \phi(||X - Cn||, \sigma n)$ where $\phi n(.)$ is a radial basis function (RBF) localized around Cn.

$$\phi(Z, \sigma) = exp \frac{Z^2}{2\sigma^2}$$


Input layer
Output layer
Sub-synapses

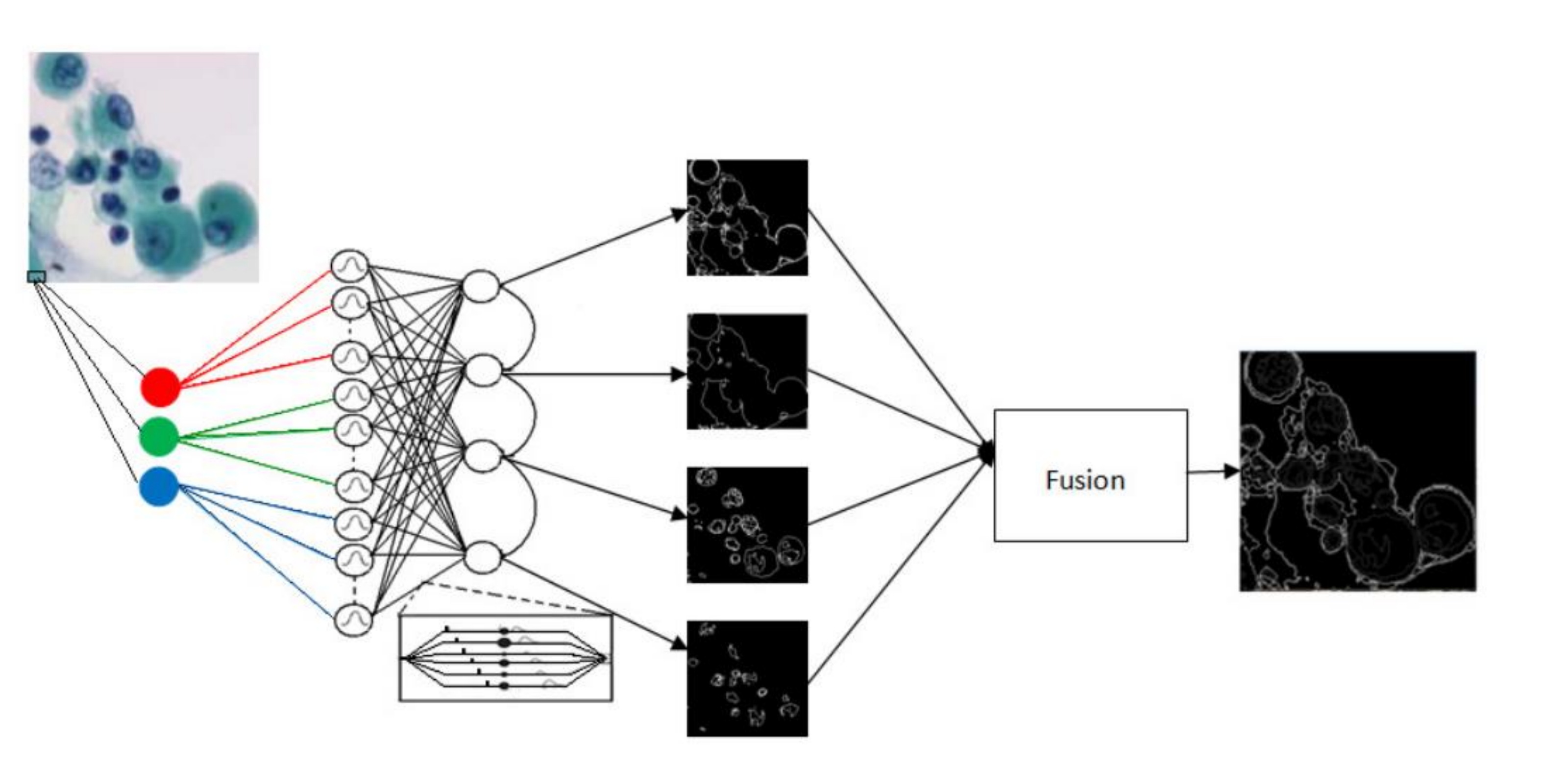
- This synapse model consists of many sub-synapses, each one with its own weight and delay dk
- For each multiple synapse connecting neuron i to neuron j, with s subsynapses(results in PSP)
- The neuron model implemented is the SRM0 (Gerstner, 2002), with a strictly excitatory PSP. The delays dk are fixed for all sub-synapse k, varying from zero in 1ms fixed intervals. $\varepsilon(t)$ modeling a simple α-function.

SNN ARCHITECTURE FOR CELL SEGMENTATION

- The network architecture consists in a fully connected feedforward network of spiking neurons with connections implemented as multiple delayed synaptic terminals
- the SNN performs its learning directly on the pixels of the image to classify
- The first layer is composed of RGB values of pixels.
- Each node in the hidden layer has a localized activation n where n (.) is a radial basis function (RBF) localized around cn with the degree of localization parameterized by n.

SNN ARCHITECTURE FOR EDGE DETECTION

- First image of a microscopic cell is segmented with spiking neural network. Once the segmentation done, we will record the activity of each output neuron which gives for each input pixel an output binary 1 if the neuron is active or 0 if the neuron is inactive. The result of binary matrices activation of output neurons can be represented by binary images containing the edges detected by these neurons for each class. Fusion is then made to have the final edges by superimposing the resulting images


Fusion