Cognitive Systems Engineering

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Cognitive System Engineering

Cognitive systems (CogSys) are software-hardware systems that have their structure and functionality based on principles of information processing in the human brain. They are part of AI, but AI includes also other systems that manifest cognitive behaviour, such as speech and image recognition, learning and reasoning, but using other methods , such as statistical, empirical, abstract logic , etc.

The course is by research papers.
Every topic will include:

1. Topic/task/problem specification
2. Previously published methods for solving the problem
3. Description of the method and in the paper under discussion
4. Software implementation, experimental results and discoveries
5. Applications
6. Future work to be done for this problem and questions for individual work

Expected results:

1. Students obtain new knowledge and skills in the area of CogSys for AI applications.
2. Students can learn to take a critical approach to the existing methods and systems.
3. Students can get confidence that they can suggest new methods and to publish them in good journals.

Additional materials: https://www.knowledgeengineering.ai/china
ZOOM link for all lectures:
https://us05web.zoom.us/j/4658730662?pwd=eFN0eHRCN3o4K0FaZ0lqQmN1UUgydz09

CogSysEn: Lecture Topics

1. Introduction to the course

Part I : Learning systems

2. Deep learning and deep knowledge representation in the human brain

-Chapter 3 from: N.Kasabov, Time-space, spiking neural networks and brain-inspired artificial intelligence, Springe-Nature, 2029

3.Modelling brain dynamics

- Benuskova, L., Kasabov, N. Modeling brain dynamics using computational neurogenetic approach. Cogn Neurodyn 2, 319–334 (2008). https://doi.org/10.1007/s11571-008-9061-1

4. Evolving learning systems

- N. Kasabov, "Evolving fuzzy neural networks for supervised/unsupervised online knowledge-based learning," in IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 31, no. 6, pp. 902-918, Dec. 2001, doi: 10.1109/3477.969494.

- NeuCom software (https://theneucom.com): EFuNN

5. Neuro—fuzzy learning and inference systems: DENFIS

- Kasabov, N. K., & Song, Q. (2002). DENFIS: dynamic evolving neural-fuzzy inference system and its application for time-series prediction. IEEE transactions on Fuzzy Systems, 10(2), 144-154.

- DENFIS software in Python.

6. Spatio-temporal learning systems: SNN

- N. Kasabov, K. Dhoble, N. Nuntalid, G. Indiveri, Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. Neural Networks, 41(1995), 188–201 (2013). https://doi.org/10.1016/j.neunet.2012.11.014.

- Software deSNN

7. Reservoir computing and Brain-inspired SNN

- S. Schliebs, A. Mohemmed, N. Kasabov, Are probabilistic spiking neural networks suitable for reservoir computing? in International Joint Conference on Neural Networks (San Jose, USA, 2011), pp. 3156–3163.

- N. Kasabov, NeuCube: a spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data. Neural Netw. 52(2014), 62–76 (2014).

8. Integrated learning systems:

- *P. Koprinkova-Hristova, D. Penkov, S. Nedelcheva, S. Yordanov and N. Kasabov, "On-line Learning, Classification and Interpretation of Brain Signals using 3D SNN and ESN," 2023 International Joint Conference on Neural Networks (IJCNN), Gold Coast, Australia, 2023, pp. 1-6, doi: https://doi.org/10.1109/IJCNN54540.2023.10191974,*

- AbouHassan et al, *NeuDen: Integrating evolving Neuromorphic spiking neural networks and Dynamic evolving neuro-fuzzy systems for predictive and explainable learning of multiple time series*

Lecture 6: Spatio-temporal learning systems in SNN

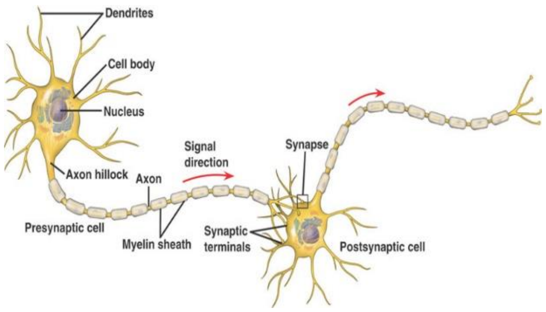
- N. Kasabov, K. Dhoble, N. Nuntalid, G. Indiveri, Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. Neural Networks, 41(1995), 188–201 (2013). https://doi.org/10.1016/j.neunet.2012.11.014.
- Software deSNN

1. **Spatio-temporal learning is a cognitive feature that we aim to represent in a computational model**

- when two objects are connected in space, with a directed connection from the first to the second, and activated one after another in time, with the first object activated first and then the second object, there is a positive temporal association between them;

- … with the second object activated first and then the first object, there is a negative temporal association/correlation between them;

Strong positive connections may represent causality;



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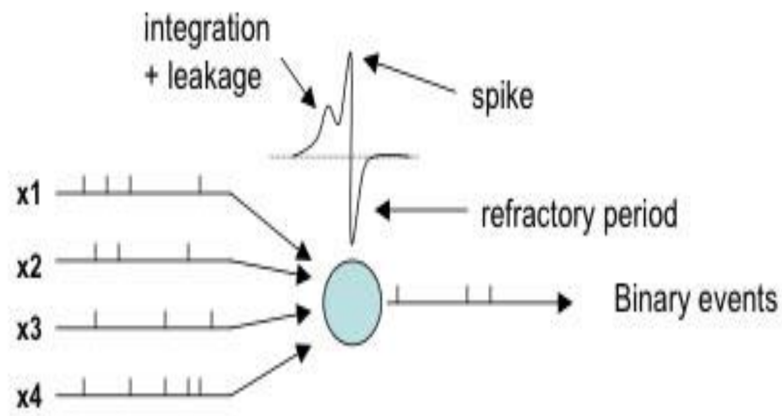
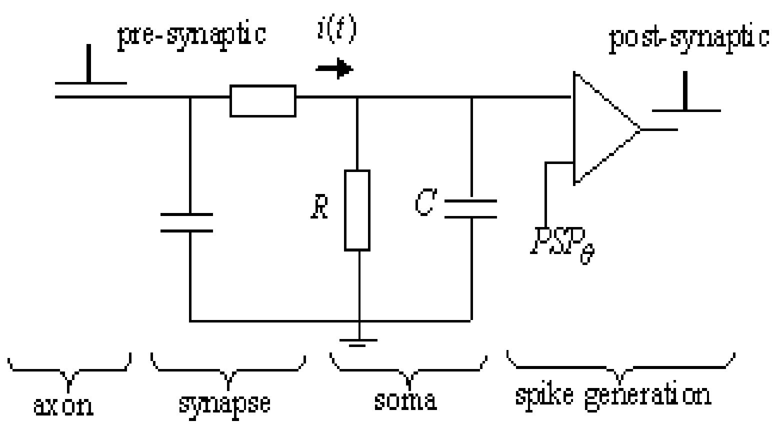
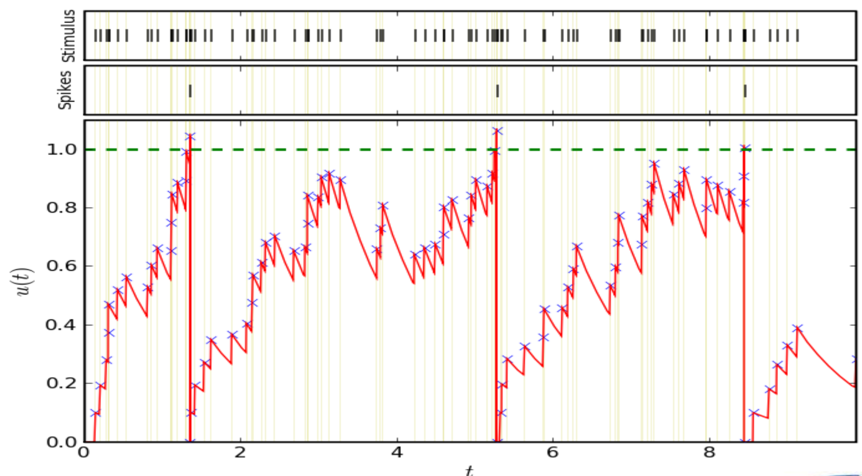
2. **Spiking neuron models and STDP**

Models of a spiking neurons and SNN

- Hodgkin- Huxley
- Spike response model
- Integrate-and-fire ---------------->
- Leaky integrator
- Izhikevich model
- Probabilistic and neurogenetic models

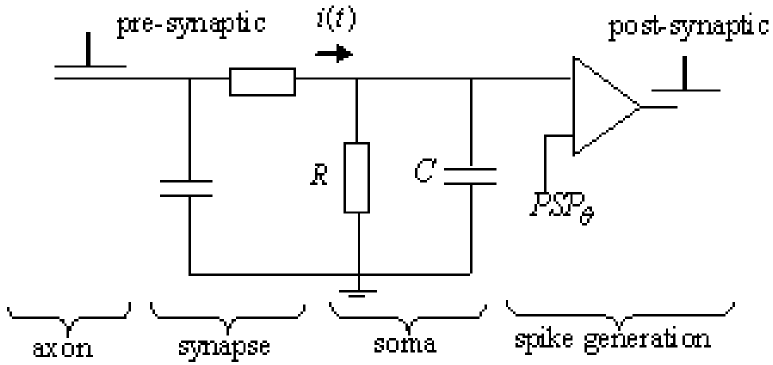






Leaky Integrate-and-Fire Neuronal Model

- Model consists of capacitor *C* in parallel with resistor *R*, driven by a current $I(t) = I_R + I_{cap}$



Standard form of the model:

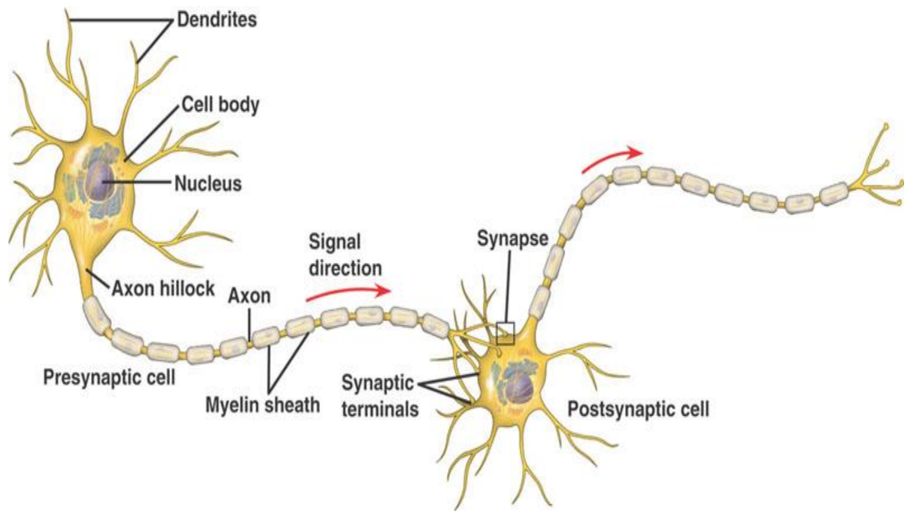
$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$

- $\tau_m = RC$ is the membrane time constant
- Shape of action potentials are not explicitly modeled
- Spikes are events characterized by a firing time $t^{(f)}$: $u(t^{(f)}) = \vartheta$
- After $t^{(f)}$ the potential is reset to a resting potential u_r
- In a more general form the LIF model can also include a refractory period, in which the dynamics are interrupted for an absolute time Δ^{abs}

Methods for unsupervised learning in SNN

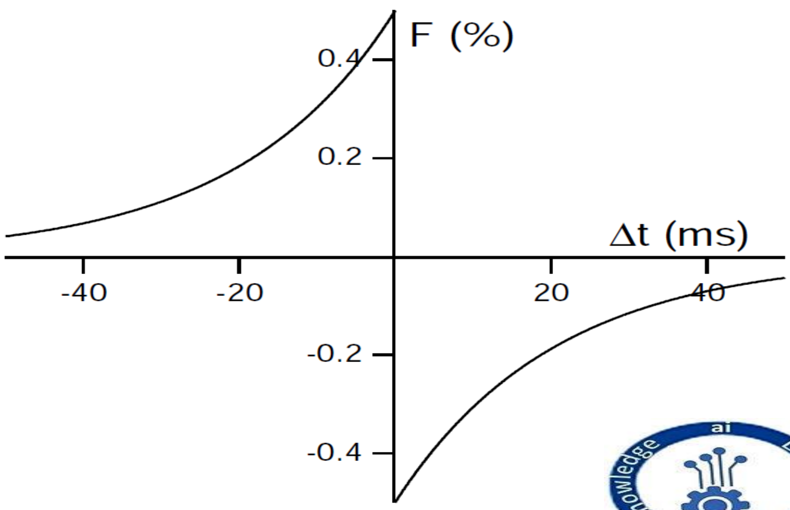
Spike-Time Dependent Plasticity (STDP)
(Abbott and Nelson, 2000).

- Hebbian form of plasticity in the form of long-term potentiation (LTP) and depression (LTD)
- Effect of synapses are strengthened or weakened based on the timing of pre-synaptic spikes and post-synaptic action potential.
- Through STDP connected neurons learn consecutive temporal associations from data.
- Variations of the STDP



Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD:

$\Delta t = t_{pre} - t_{post}$



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3. Evolving SNN and dynamic evolving SNN (deSNN) for supervised learning

- eSNN: ~ for spiking neurons (Wysoski, Benuskova, Kasabov, 2006-2010);
- Uses the first spike principle (Thorpe et al.) for fast on-line training
- For each input vector

  a) Create (evolve) a new output spiking neuron and its connections

  b) Propagate the input vector into the network and train the newly created neuron

$$u_i(t) = \begin{cases} 0 & \text{if fired} \\ \sum_{j|f(j)<t} w_{ji} m_i^{\text{order}(j)} & \text{else} \end{cases}$$

$$\Delta w_{ji} = m^{\text{order}(j)}$$

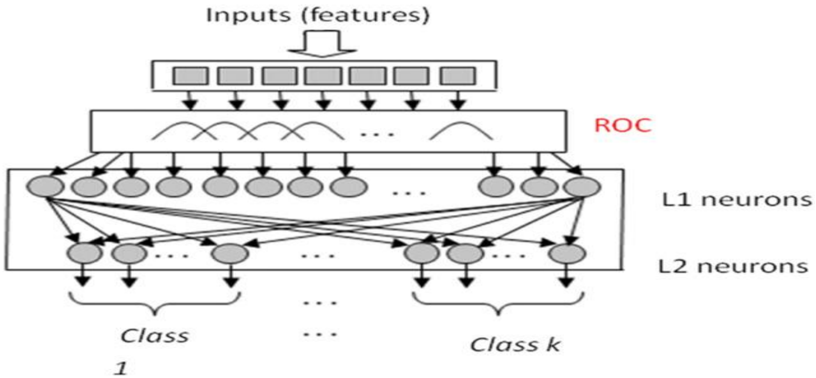
Weights change based on the order of spike time arrival

  c) : IF similarity between a new and old neurons > Threshold THEN merge neurons

$$W \Leftarrow \frac{W_{new} + NW}{1+N} \qquad \vartheta \Leftarrow \frac{\vartheta_{new} + N\vartheta}{1+N}$$

where N is the number of samples previously used to update the respective neuron.

  d) Update the corresponding threshold ϑ:



Dynamic Evolving SNN (deSNN)

(*Kasabov, N., Dhoble, K., Nuntalid, N., G. Indiveri, Dynamic Evolving Spiking Neural Networks for On-line Spatio- and Spectro-Temporal Pattern Recognition, Neural Networks, v.41, 188-201, 2013)*

Combine: (a) RO learning for weight initialisation based on the first spikes:

$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

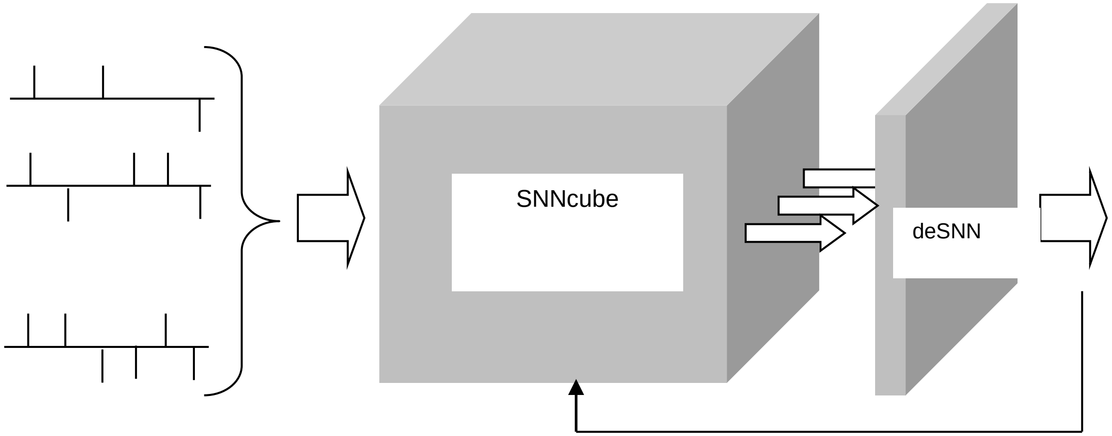
(b) Learning further input spikes at a synapse through a drift – positive and negative.

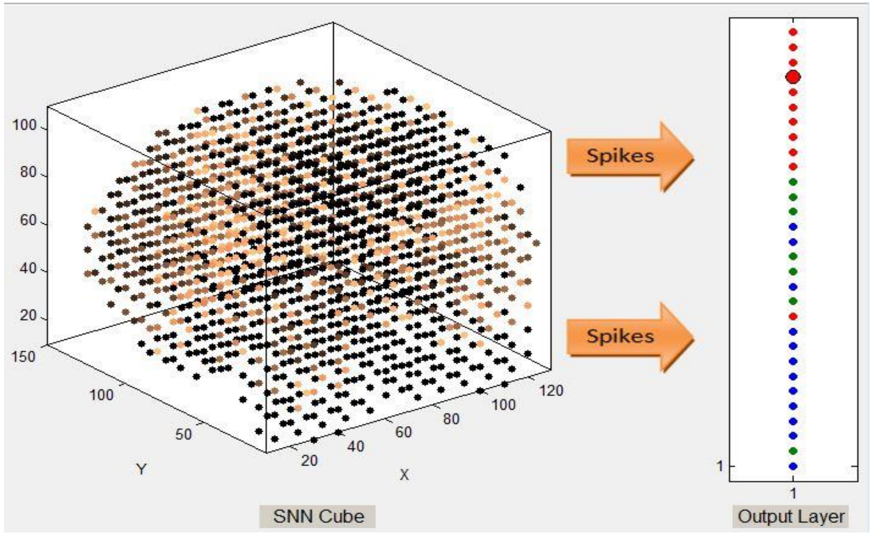
$$w_{j,i}(t) = e_j(t) \cdot \mathrm{Drift}$$

- A new output neuron may be added to a respective output repository for every new -input pattern.
- Two types of output neuron activation:
  - deSNNm (spiking is based on the membrane potential)
  - deSNNs (spiking is based on synaptic similarity between the newly created output neuron and the existing ones)
- Neurons may merge.

4. deSNN software

- As part of NeuCube: https://kedri.aut.ac.nz/NeuCubePy
- https://github.com/KEDRI-AUT/NeuCube-Py
- Appendix to the paper

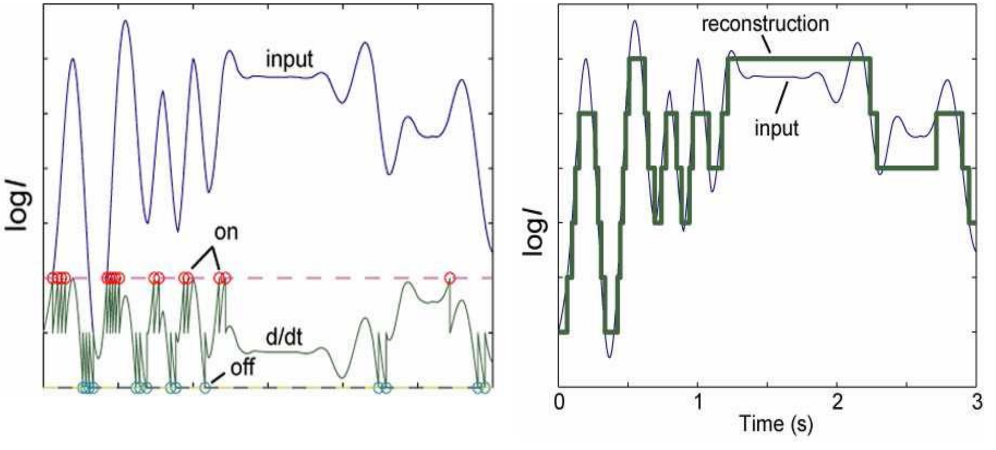




5. Applications

- classification/prediction of spatio-temporal data

- moving object recognition with the use of DVS Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128:



Threshold-based encoding – retinotopic

Examples (© Institute for Neuroinformatics, ETH Zurich)