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Brain-Inspired Spiking Neural Networks for Life-Long and Explainable Learning

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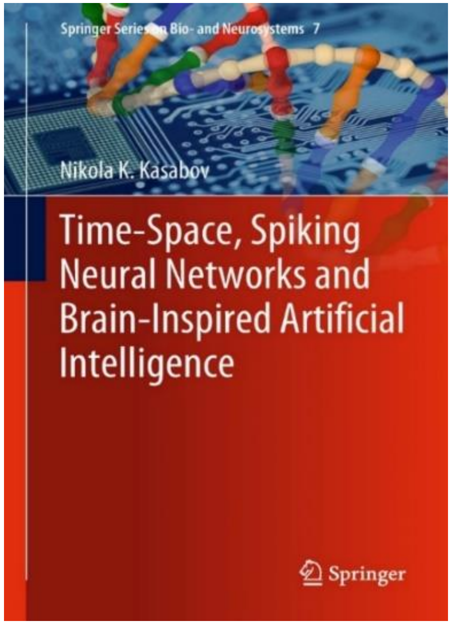
Abstract

The talk argues that the third generation of artificial neural networks, the spiking neural networks (SNN), can be used to design brain-inspired architectures that are capable of deep, incremental and life-long learning of temporal or spatio-temporal data and of extraction of deep knowledge representation from the learned data.

1. Why brain-inspired computation?
2. BI-SNN architectures. NeuCube.
3. Implementations of BI-SNN
4. Application specific methods and systems
5. Discussions and future work



Reference:
N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019), https://www.springer.com/gp/book/9783662577134

1. **Why brain-inspired computation?**

The human brain, the most sophisticated product of the evolution, is a live-long learning system for knowledge representation and knowledge transfer.

The brain (80bln neurons, 100 trillions of connections, 200 mln years of evolution) is the ultimate learning machine

Three, mutually interacting, memory types:

- short term (membrane potential);
- long term (synaptic weights);
- genetic (genes in the nuclei).

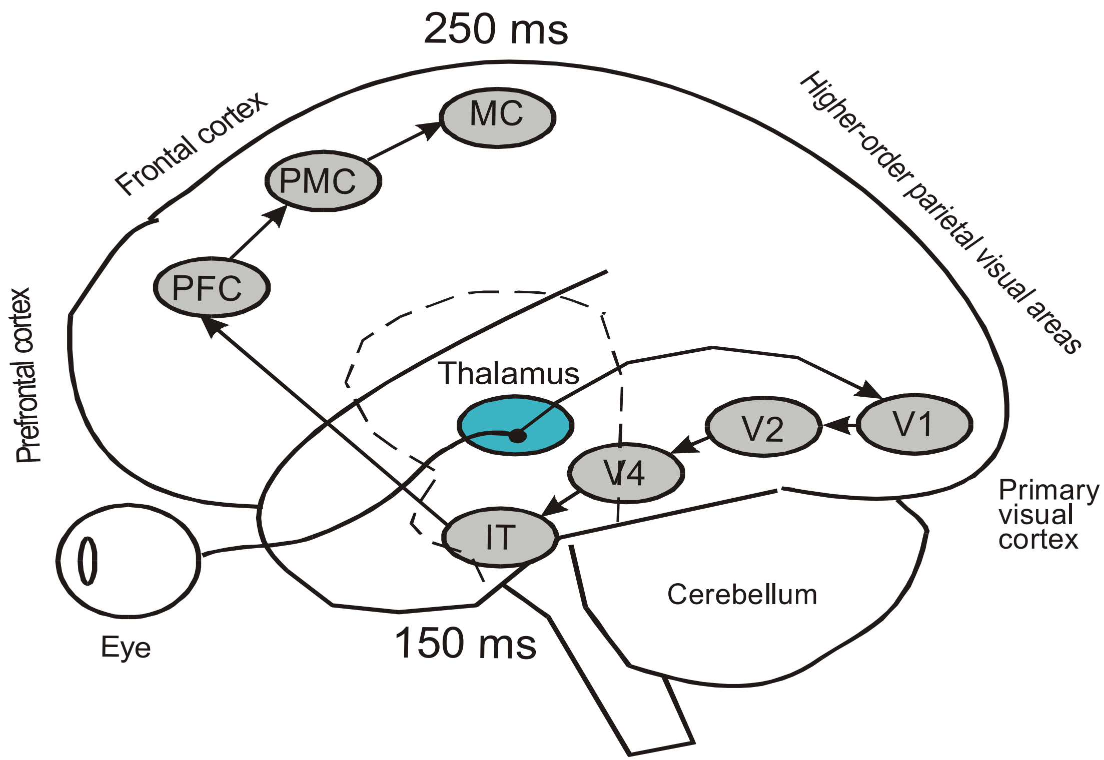
Temporal data at different time scales:

- Nanoseconds: quantum processes;
- Milliseconds: spiking activity;
- Minutes: gene expressions;
- Hours: learning in synapses;
- Many years: evolution of genes.

Knowledge is represented as deep spatio-temporal patterns that can evolve/adapt over time.

The challenge is to be able to use brain-inspired principles for life-long and explainable learning in intelligent systems.

Knowledge of seeing an object and grasping it is learned *incrementally* as a deep *spatio-temporal trajectory of connections* between clusters of neurons in the brain

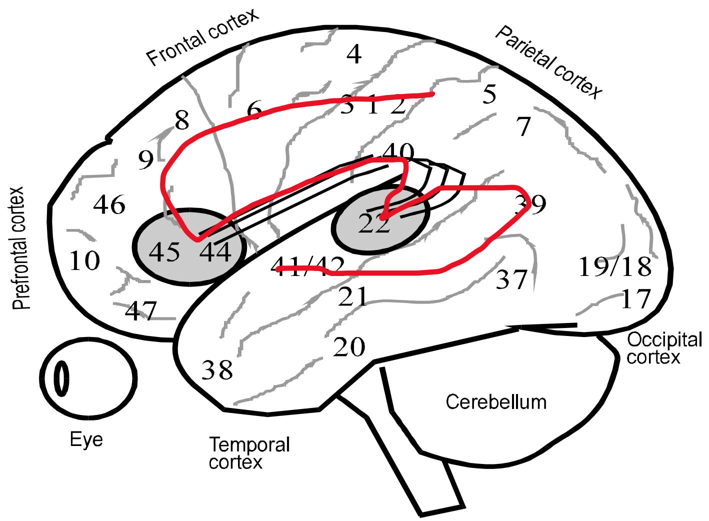


Deep serial processing of visual stimuli in humans for image classification and action.

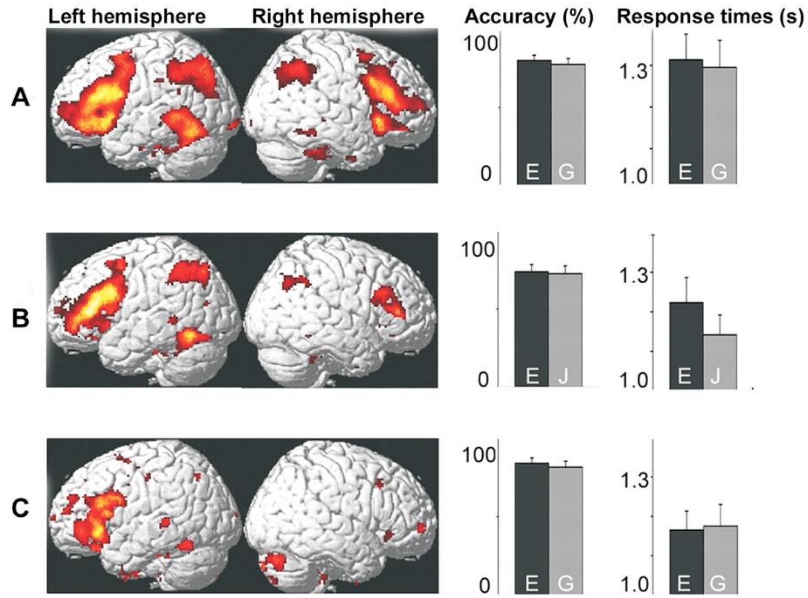
Location of cortical areas: V1 = primary visual cortex, V2 = secondary visual cortex, V4 = quartiary visual cortex, IT = inferotemporal cortex, PFC = prefrontal cortex, PMC = premotor cortex, MC = motor cortex.

(from L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer,

Speech and language in the brain



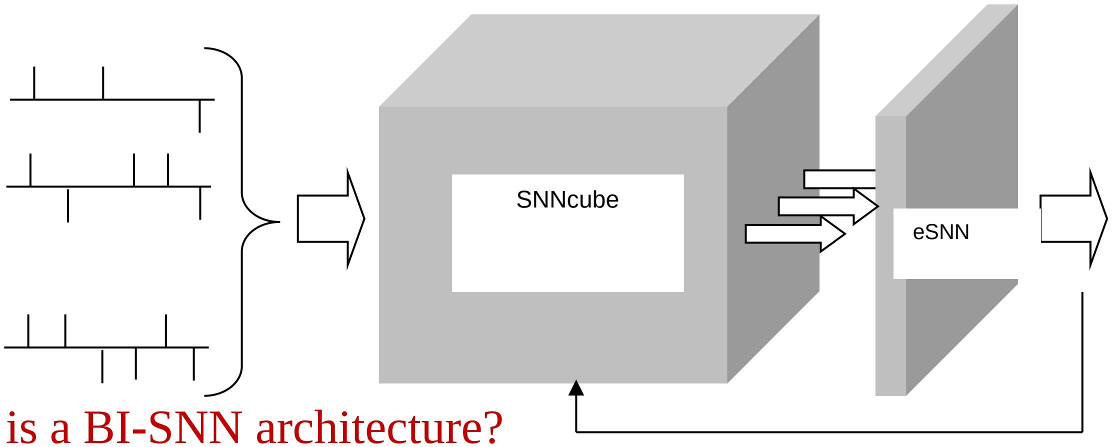
(from L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer, 2007)

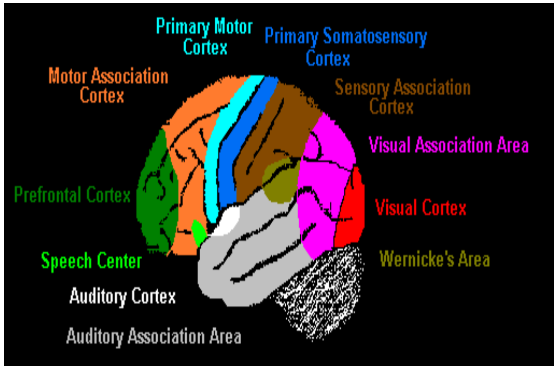


Common brain activation areas in bilingual subjects (Crinion et al, Science, 2006)

The basic model of language processing during the simple task of repeating the word that has been heard is the Wernicke-Geschwind model (Mayeux and Kandel 1991). A language task involves transfer of information from the inner ear through the auditory nucleus in thalamus to the primary auditory cortex (Brodmann's area 41), then to the higher-order auditory cortex (area 42), before it is relayed to the angular gyrus (area 39). From here, the information is projected to Wernicke's area (area 22) and then, by means of the *arcuate fasciculus*, to Broca's area (44, 45), where the perception of language is translated into the grammatical structure of a phrase and where the memory for word articulation is stored. This information about the sound pattern of the phrase is then relayed to the facial area of the motor cortex that controls articulation so that the word can be spoken.

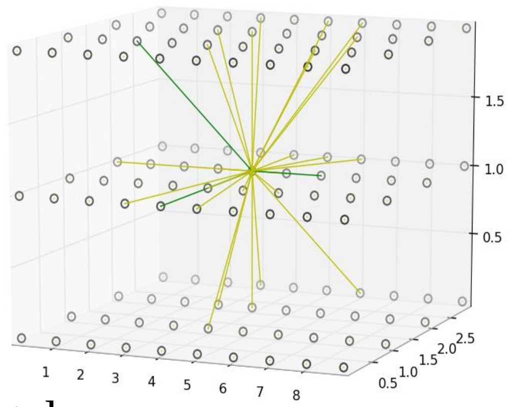
2. Brain-inspired SNN architectures (BI-SNN). NeuCube.





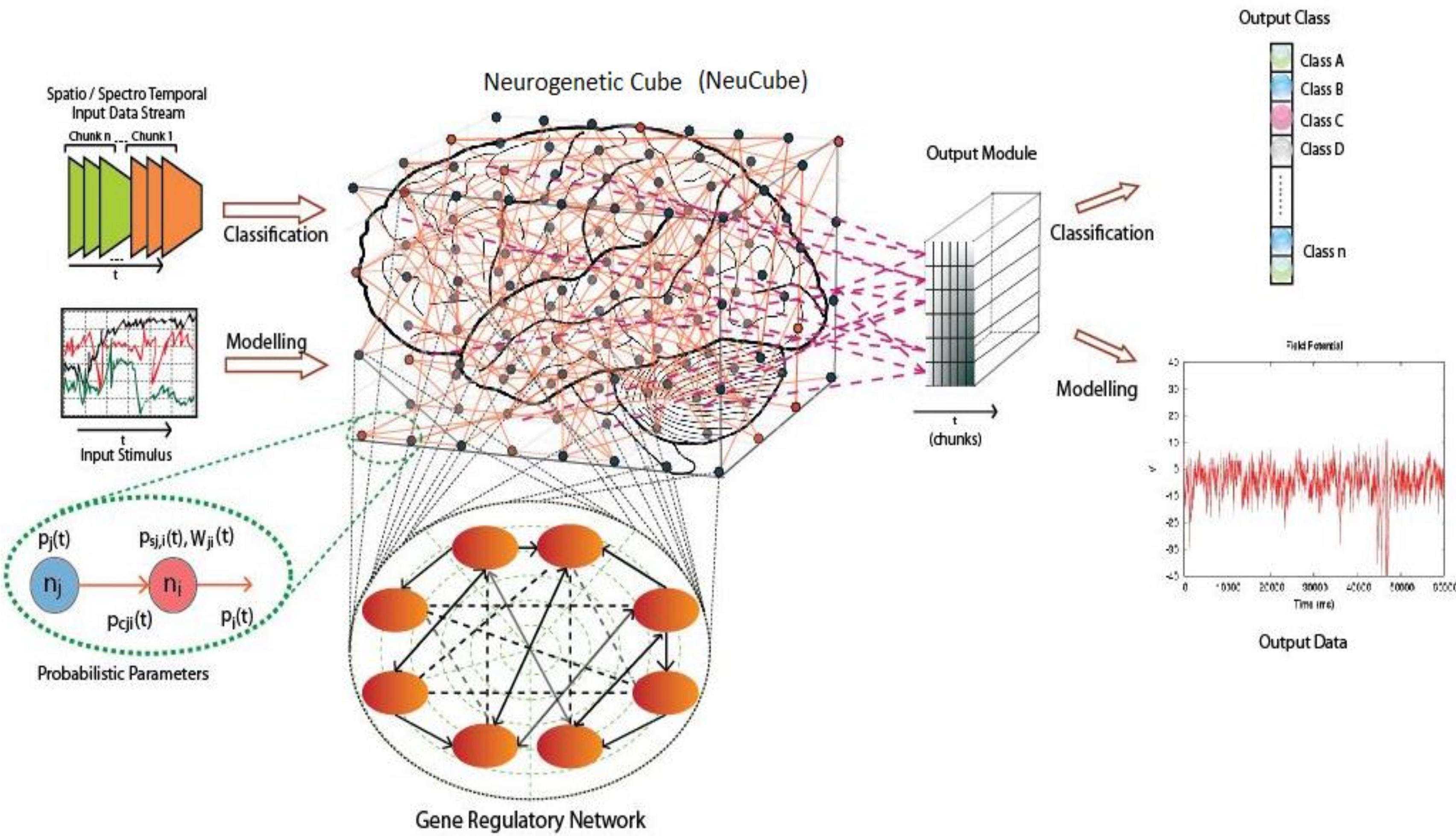
What is a BI-SNN architecture?

- Input data is encoded into spatio-temporal events as spike trains;
- A 3D SNN has spatially located neurons following a brain template, e.g Talairach, MNI etc. .
- Inputs are mapped spatially (brain-like) into the SNN, a 3D structure organised as a brain template.
- Unsupervised learning is spatio-temporal, adaptive and incremental resulting in evolved connectivity
- The structure is self-organising
- Supervised learning is evolving creating new output neurons
- Allows for knowledge representation as spatio-temporal patterns, interpreted as rules, graphs, associations, ….



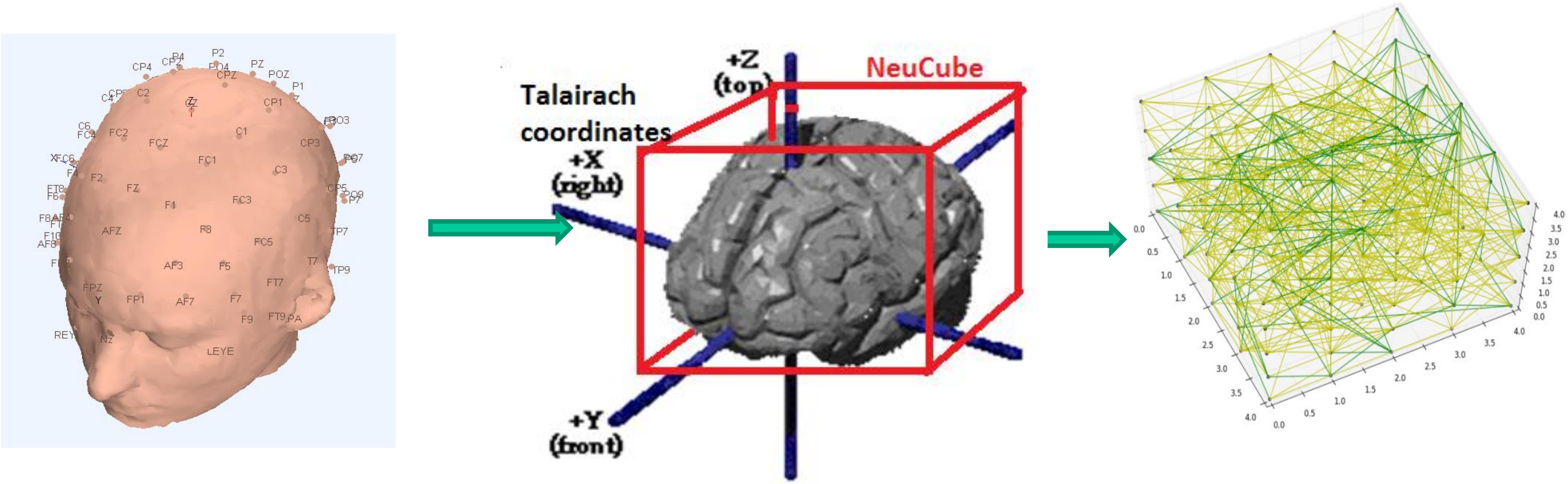
$$p_{a,b} = C \times e^{-D^2_{a,b}/\lambda^2}$$

The NeuCube Architecture: **10 Years of NeuCube**



Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

Mapping a brain template into a 3D SNNcube



Further development of ideas from SOM (Kohonen) and ART (Grossberg)

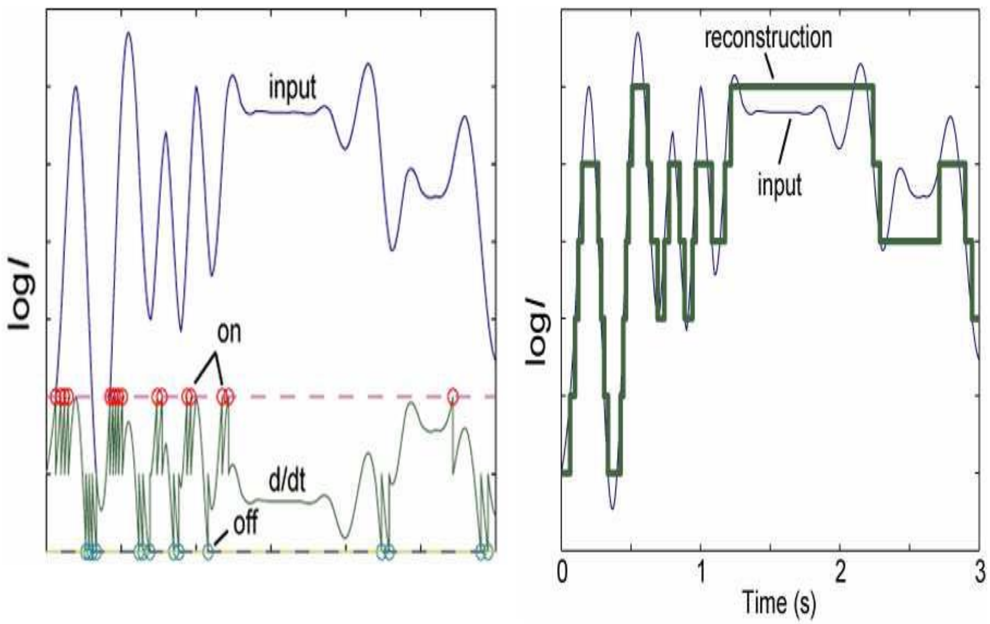
E. Tu, N. Kasabov, J. Yang, Mapping Temporal Variables into the NeuCube Spiking Neural Network Architecture for Improved Pattern Recognition and Predictive Modelling, IEEE Trans. on Neural Networks and Learning Systems, 28 (6), 1305-1317,, 2017 DOI: 10.1109/TNNLS.2016.2536742, 2017.

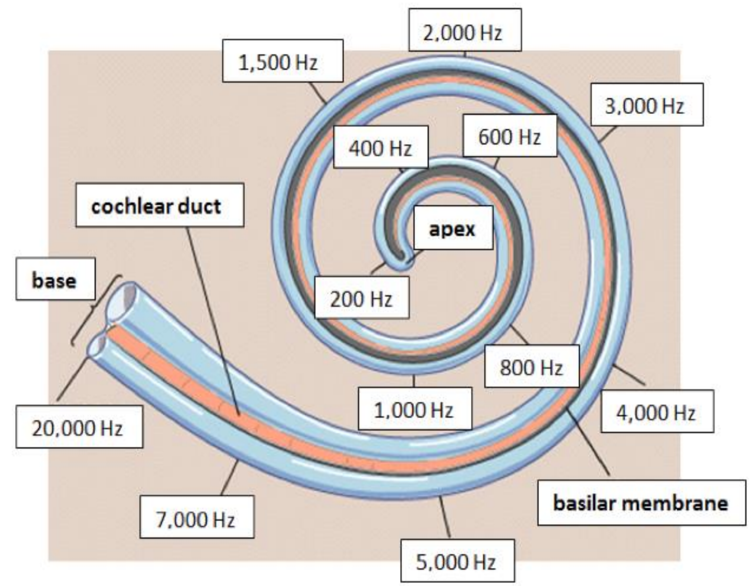
Spike encoding methods

A spike is generated only if a change in the input data occurs beyond a threshold

Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128: Retinotopic

Silicon Cochlea (Shih-Chii Liu, INI, ETH/UZH, Zurich): Tonotopic





Threshold-based encoding – retinotopic mapping for spatio-temporal data

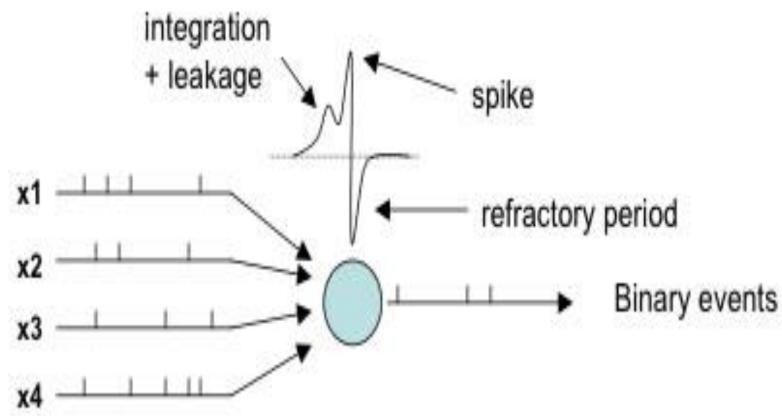
Tonotopic organization of the cochlea for spectro-temporal data

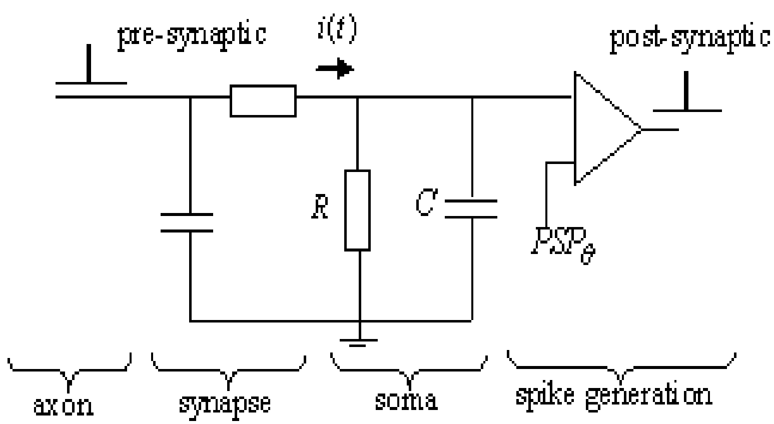
https://sites.google.com/site/jayanthinyswebite

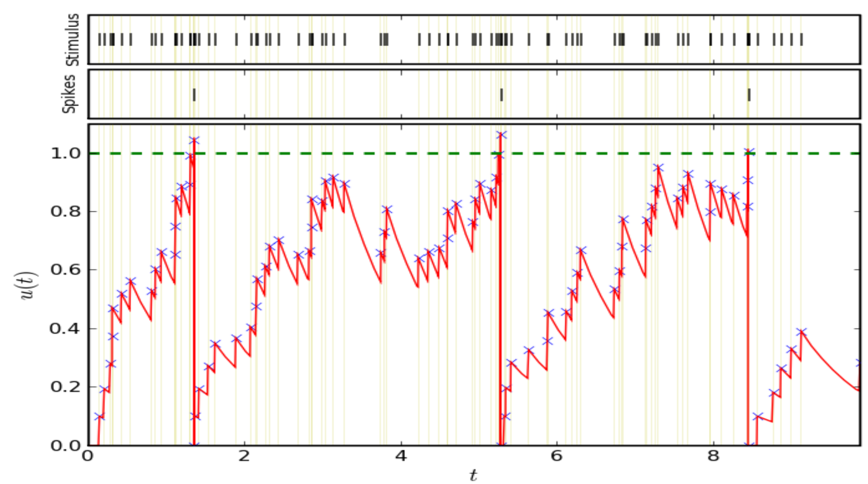
Spiking neuron models for BI-SNN

Models of a spiking neurons and SNN

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



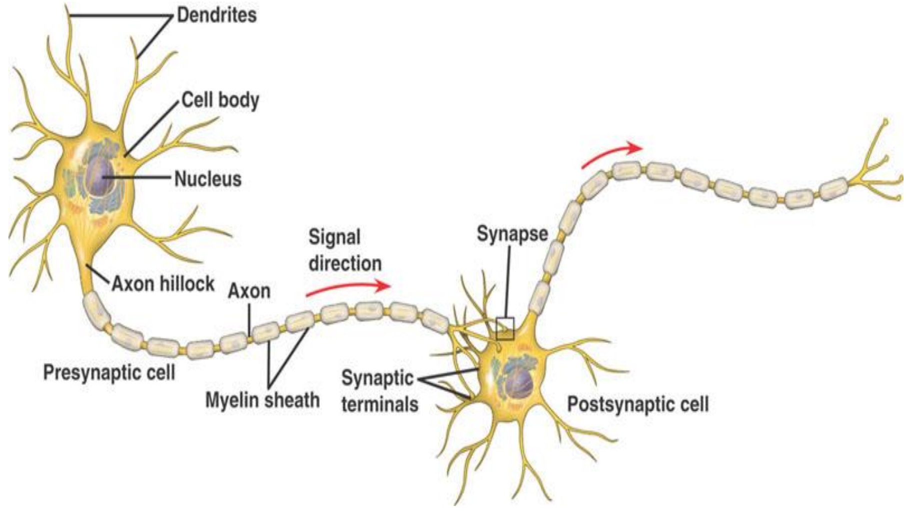




Methods for unsupervised learning in SNN

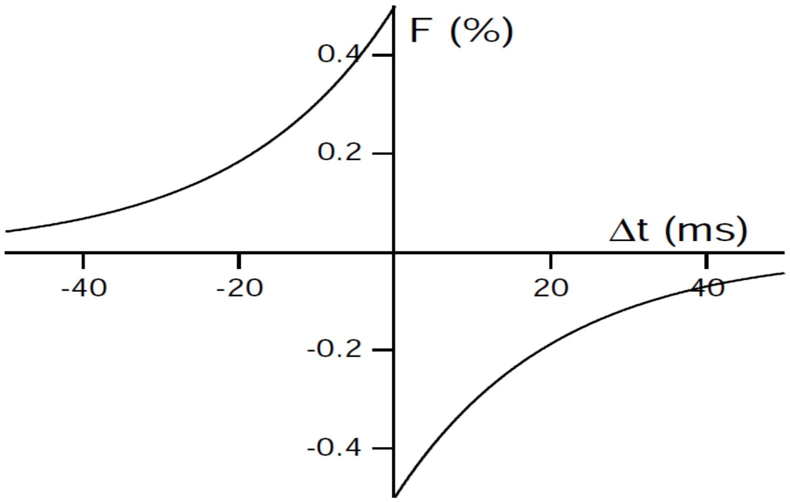
Spike-Time Dependent Plasticity (STDP)
(Abbott and Nelson, 2000).

- 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



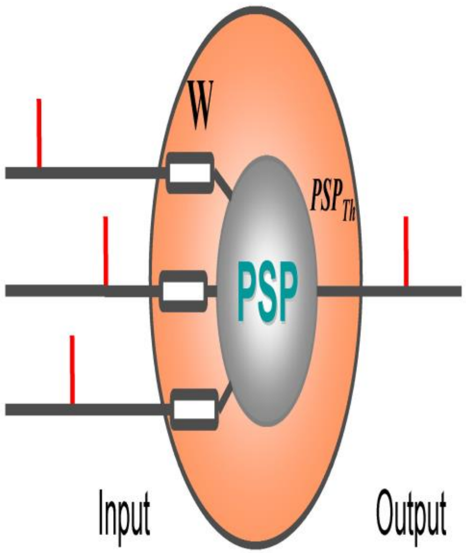
Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD:

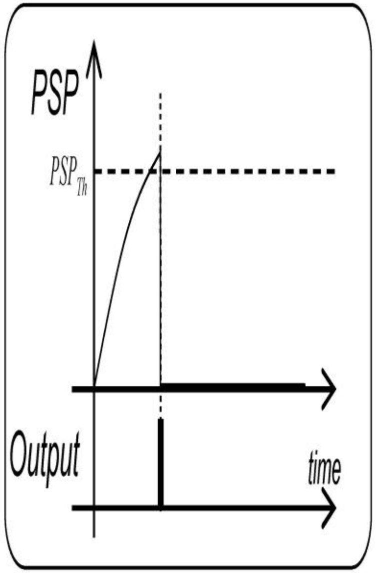
Δt=tpre -tpost



Methods for supervised learning in SNN

Rank order (RO) learning rule (Thorpe et al, 1998)





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

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

PSP max (T) = SUM [($m^{\mathrm{order}\,(j(t))}$) $w_{j,i}$(t)], for j=1,2.., k; t=1,2,...,T;

PSP_{Th}=C. PSPmax (T)

- Earlier coming spikes are more important (carry more information)
- Early spiking can be achieved, depending on the parameter C.

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.

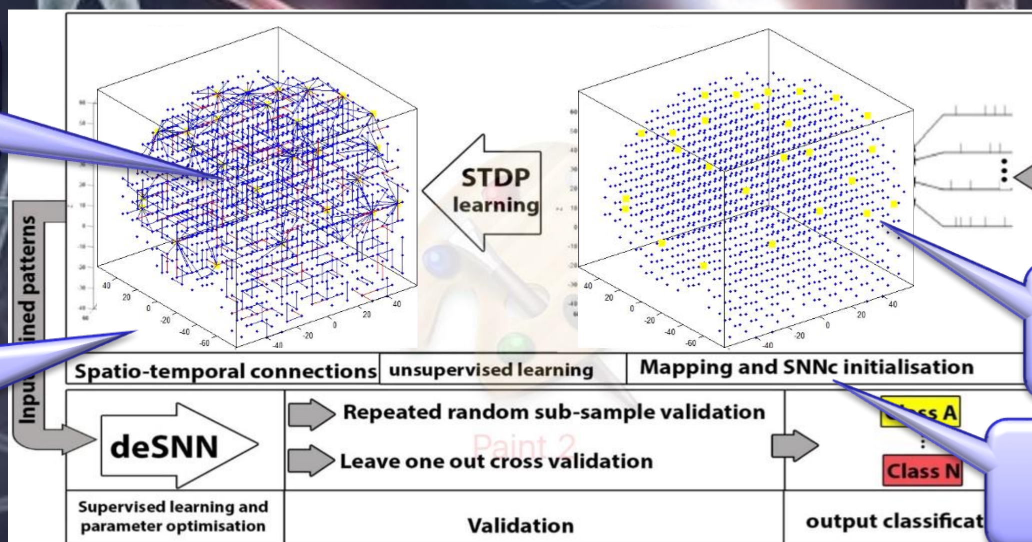
$$w_{j,i}(t) = e_j(t) \cdot \mathrm{Drift}$$

- 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.

Deep, life-long learning in NeuCube

Creation of Neuron Connections During The Learning

The More Spike Transmission, The More Connections Created



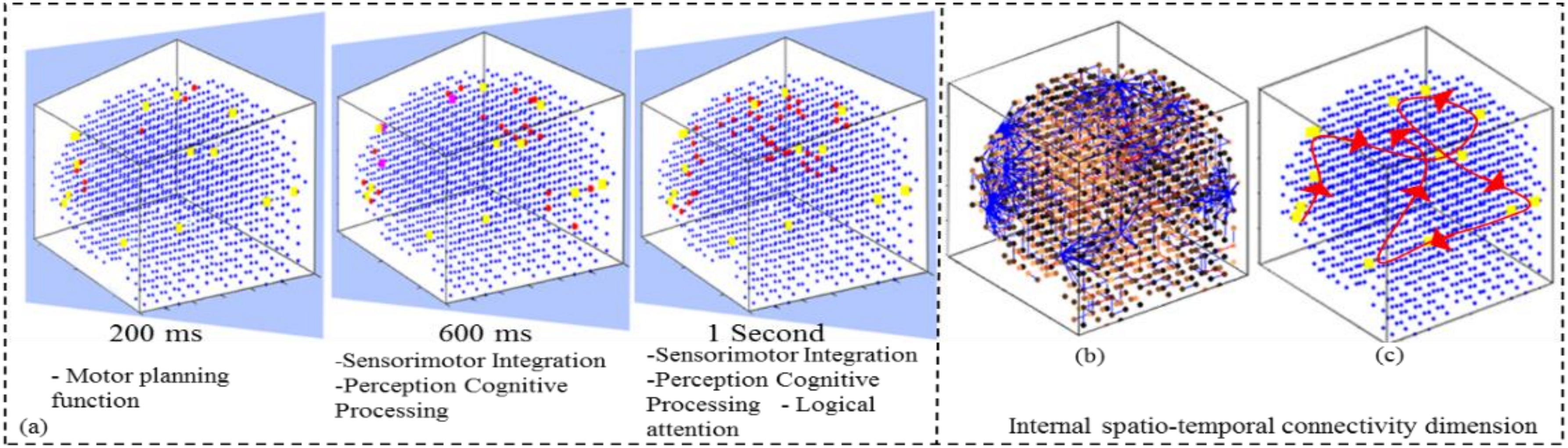
Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning

nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube/

Example

A SNNcube that learns EEG data from 14 EEG channels when a person is moving a wrist. The sequence of connections of the trained SNNcube can be interpreted as TSR. The figure is showing only few aggregated events (out of 1000, one at each millisecond EEG data).



TSR representation of time and space aggregated events:

IF (a person is moving a hand up)

THEN (the following brain functions are activated in space and time):

E1: Planning, in the Motor Planning functional brain area, time T1,

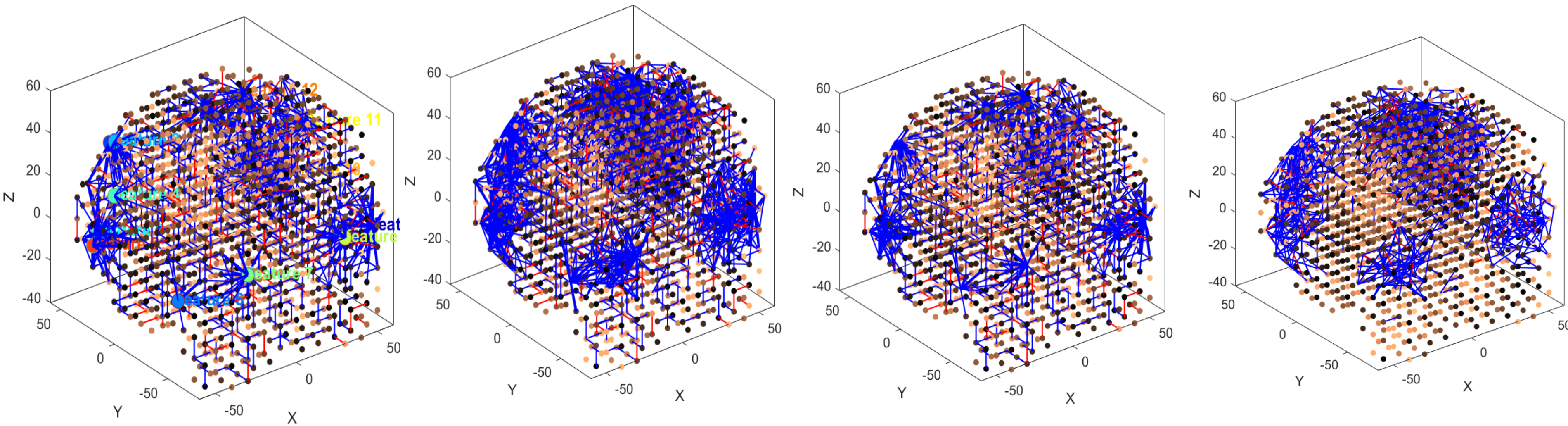
AND E2: Sensorimotor integration, in the Sensorimotor integration brain area, at time T2

AND E3: Perception, in the Perception Cognitive brain area, time T3

AND E4: Attention, in the Logical Attention brain area, time T4.

Incremental and transfer learning and knowledge evolution in BI-SNN

Example: Transfer learning of three class problem of EEG data of moving a wrist: Up, Flat, Down



(a) (b) (c) (d)

(a) Connectivity of the SNN cube trained with first two classes – model M1;

(b) SNN after the third class data is learned incrementally as model M2;

(c) The shared connections between the two models;

(d) New connections in model M2 for classification of class 3 data (threshold 0.8).

Experiments and figures are created by Dr Enmei Tu (SJTU). Data from www.kedri.aut.ac.nz/neucube/

Some principles of **Life-long Learning (LLL)** in the brain and in NeuCube

- ## How is LLL performed in the brain?

(e.g. D Kudithipudi et al H.Siegelman, Biological underpinnings for lifelong learning machines, NatMI, vol.4,2022)

Neurogenesis
Neuromodulation
Episodic replay
Metaplasticity
Multisensory integration
Multimodal higher level integration; consciousness

- ## How can LLL be achieved in NeuCube?

Spike-frequency or spike-time predictive modelling at single neurons using error backpropagation
Neuromodulatory synaptic connection
Weight regulation
Homeostasis
Lyapunov energy function
Evolving classifiers/regressors (deSNN) where neuronal outputs are evolved and aggregated continuously

Evolving spatio-temporal associative memories:

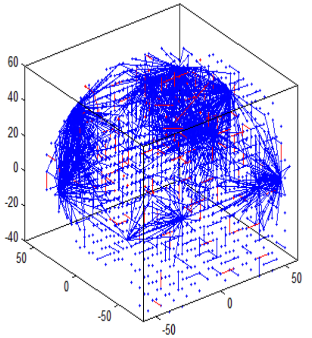
* N K Kasabov (2024) Life-long learning and evolving associative memories in brain-inspired spiking neural networks. MOJ App Bio Biomech. 2024; 8(1):56–57, https://doi.org/10.15406/mojabb.2024.08.00208.

* N K Kasabov (2024). STAM-SNN: Spatio-Temporal Associative Memory in Brain-Inspired Spiking Neural Networks: Concepts and Perspectives. In: Kovács, L., Haidegger, T., Szakál, A. (eds) Recent Advances in Intelligent Engineering. Topics in Intelligent Engineering and Informatics, vol 18. Springer, https://doi.org/10.1007/978-3-031-58257-8_1

Explainable learning in NeuCube

Time-Space Rule (TSR) representation in BI-SNN – "opening the cube"

Spatio-Temporal Rules (STR) represent ordered sequences of discrete events E={E1, E2,..., En} in space/time:



Ei =(Fi, Si, Ti, Pi),

where: Ei is event; Fi is a function; Si is the location where the function takes place; Ti is the time of the function activation; Pi is probability of the function operation.

Example:

IF (event E1: function F1, location around S1, time about T1, probability about P1)
AND (strength W1,2 between event E1 and event E2)
(event E2: function F2, location around S2, time about T2, probability about P2)
AND (strength W2,3,)
(event E3: function F3, location around S3, time about T3, probability about P3)
AND ...
. ...
(event En : function Fn, location around Sn, time about Tn, probability about Pn)
THEN (An informative cognitive/action pattern is recognized and classified).

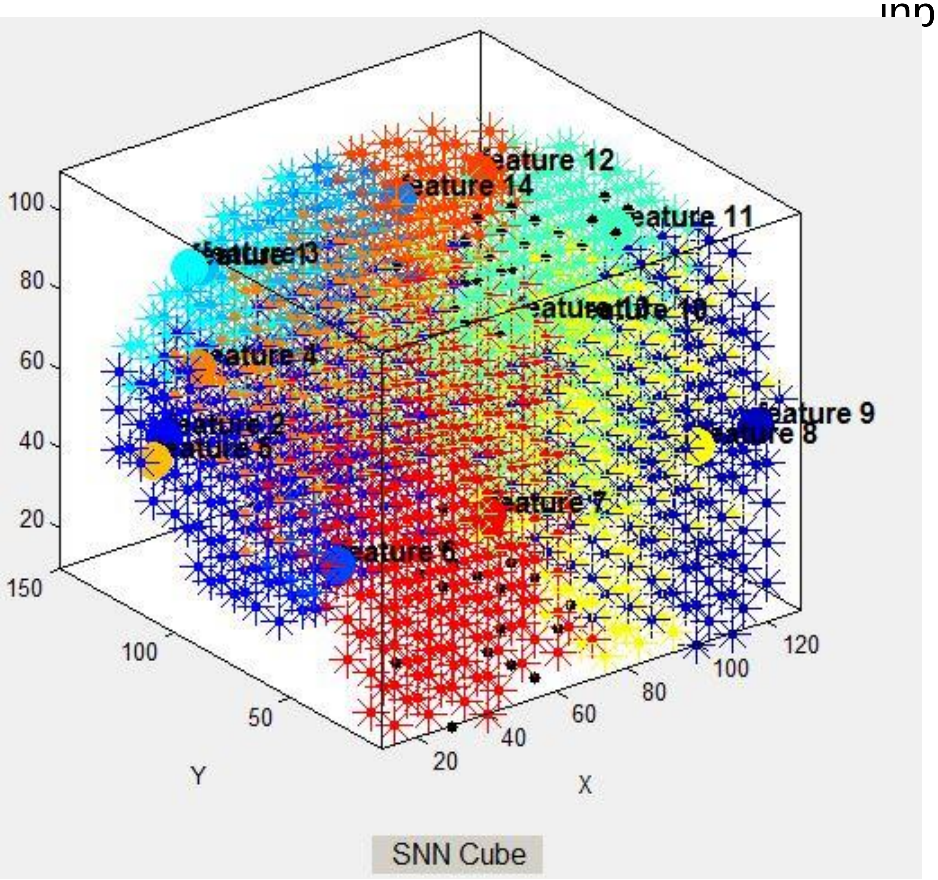
Such STR representation can be as deep as needed (e.g. from tens to millions of linked events in time-space) depending on the *granularity* of discretization.

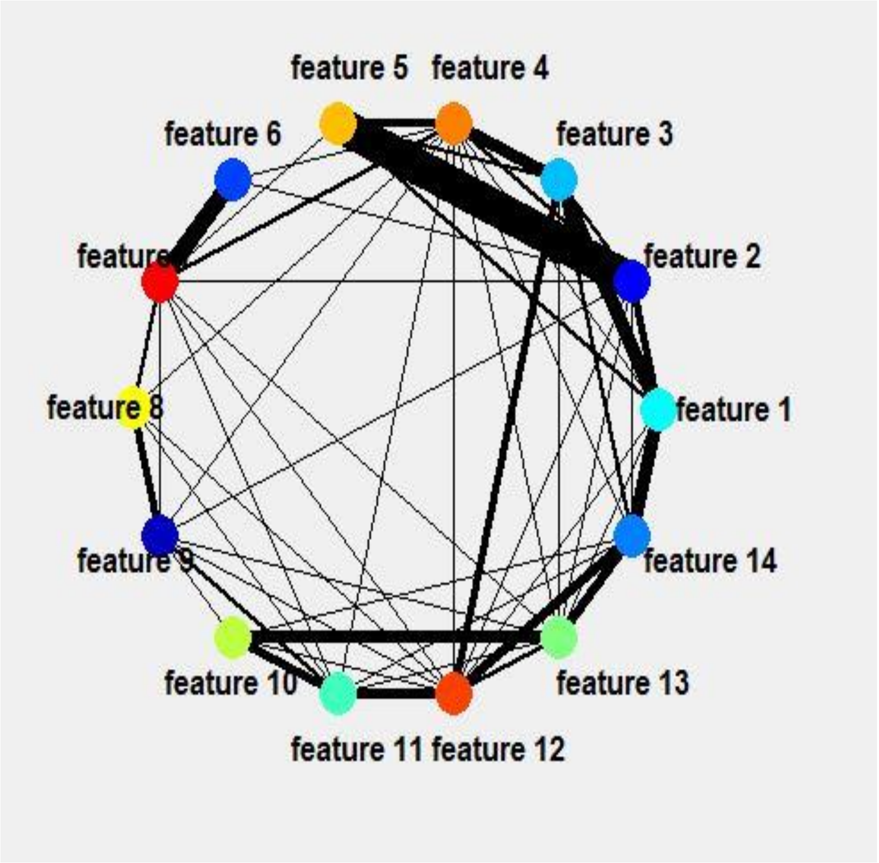
Capturing spatio-temporal knowledge as information exchange between clusters

- Clusters of highly connected neurons to input neurons;

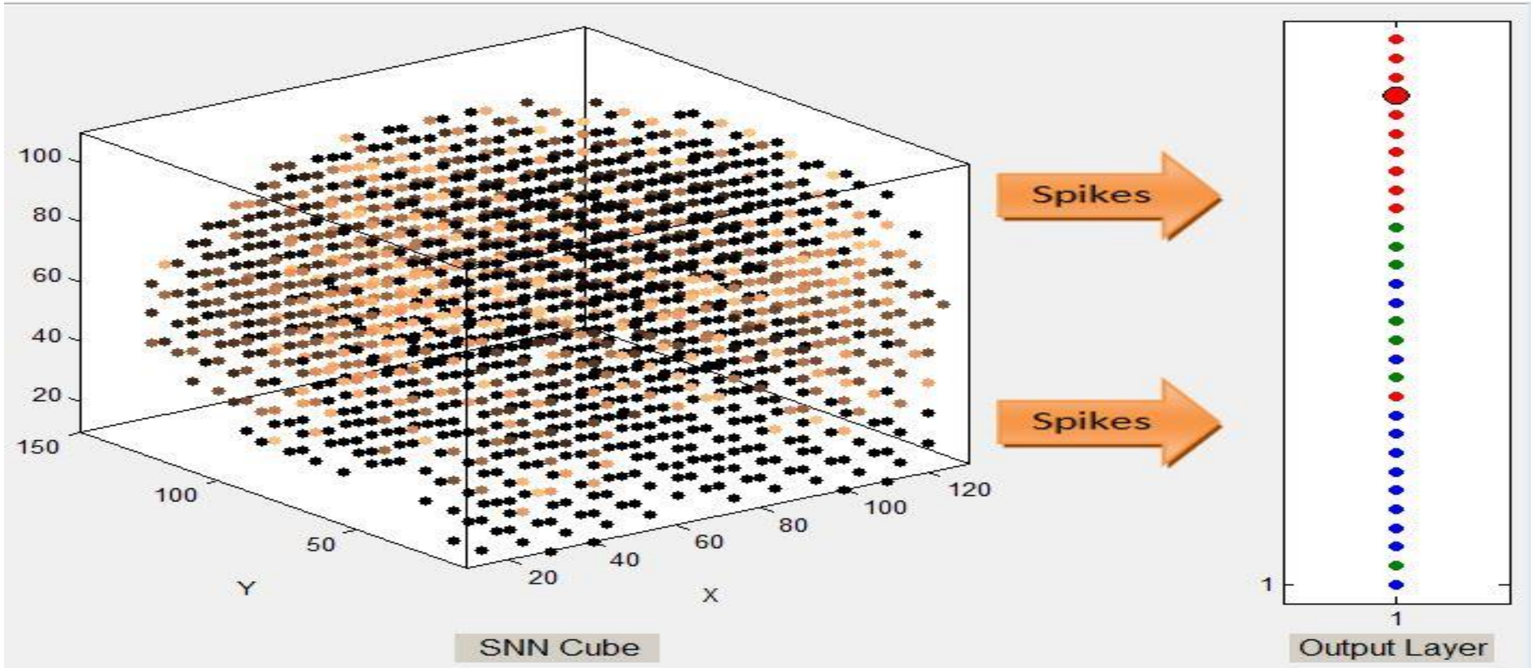
- Clusters of spiking activity spread from input neurons ;

- A dynamic graph of information exchange between spatially distributed clusters around the inputs





Capturing knowledge representation in a BI-SNN through supervised learning with deSNN



Example of TSR representation in a trained SNN classifier

IF (area (Xi,Yi,Zi) in the Cube with a cluster radius Ri is activated at time about T1) AND

(area (Xj,Yj,Zj) with a cluster radius Rj is activated at time about T2) AND

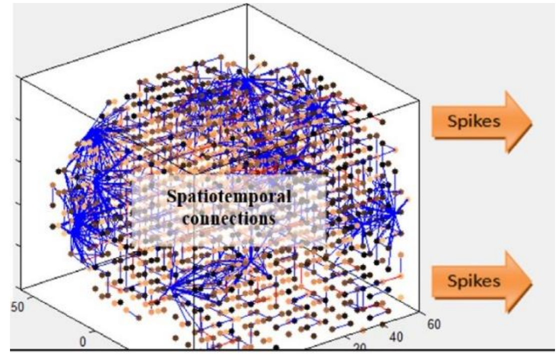
(area (Xk,Yk,Zk) with a cluster radius Rk is activated at time about T3) AND

(no other areas of the SNNcube are activated)

THEN (The output class prototype is number 4 from class 1).

Extracting Spatio-Temporal Rules (STR) from a trained NeuCube using EEG data for the GAL task

IF (event E1) AND (event E2) …THEN (Action)



IF($E_{\text{cue-onset}}$: $F_{\text{cue-onset}}$, $S\{\text{cue-onset}\}$, $t_{\text{cue-onset}}$, $P>0.8$)
AND($E_{\text{motor-planning}}$: $F_{\text{motor-planning}}$, $S_{\text{motor-planning}}$, $t_{\text{motor-planning}}$, $P>0.8$)
AND($E_{\text{movement-onset}}$: $F_{\text{movement-onset}}$, $S_{\text{movement-onset}}$, $t_{\text{movement-onset}}$, $P>0.8$)
AND($E_{\text{touch-object}}$: $F_{\text{touch-object}}$, $S_{\text{touch-object}}$, $t_{\text{touch-object}}$, $P>0.8$)
AND($E_{\text{hold-object}}$: $F_{\text{hold-object}}$, $S_{\text{hold-object}}$, $t_{\text{hold-object}}$, $P>0.9$)
AND($E_{\text{release-object}}$: $F_{\text{release-object}}$, $S_{\text{release-object}}$, $t_{\text{release-object}}$, $P>0.8$)
AND(E_{rest} : F_{rest}, S_{rest}, t_{rest}, $P>0.8$)
THEN($Q = Q_{\text{grasp-and-lift}}$).

where Si = {Posterior Lobe, Temporal Lobe, Limbic Lobe, Frontal Lobe, Anterior Lobe, Occipital Lobe, Midbrain, Parietal Lobe}

* Kasabov, N., Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2018), 750p., https://www.springer.com/gp/book/9783662577134

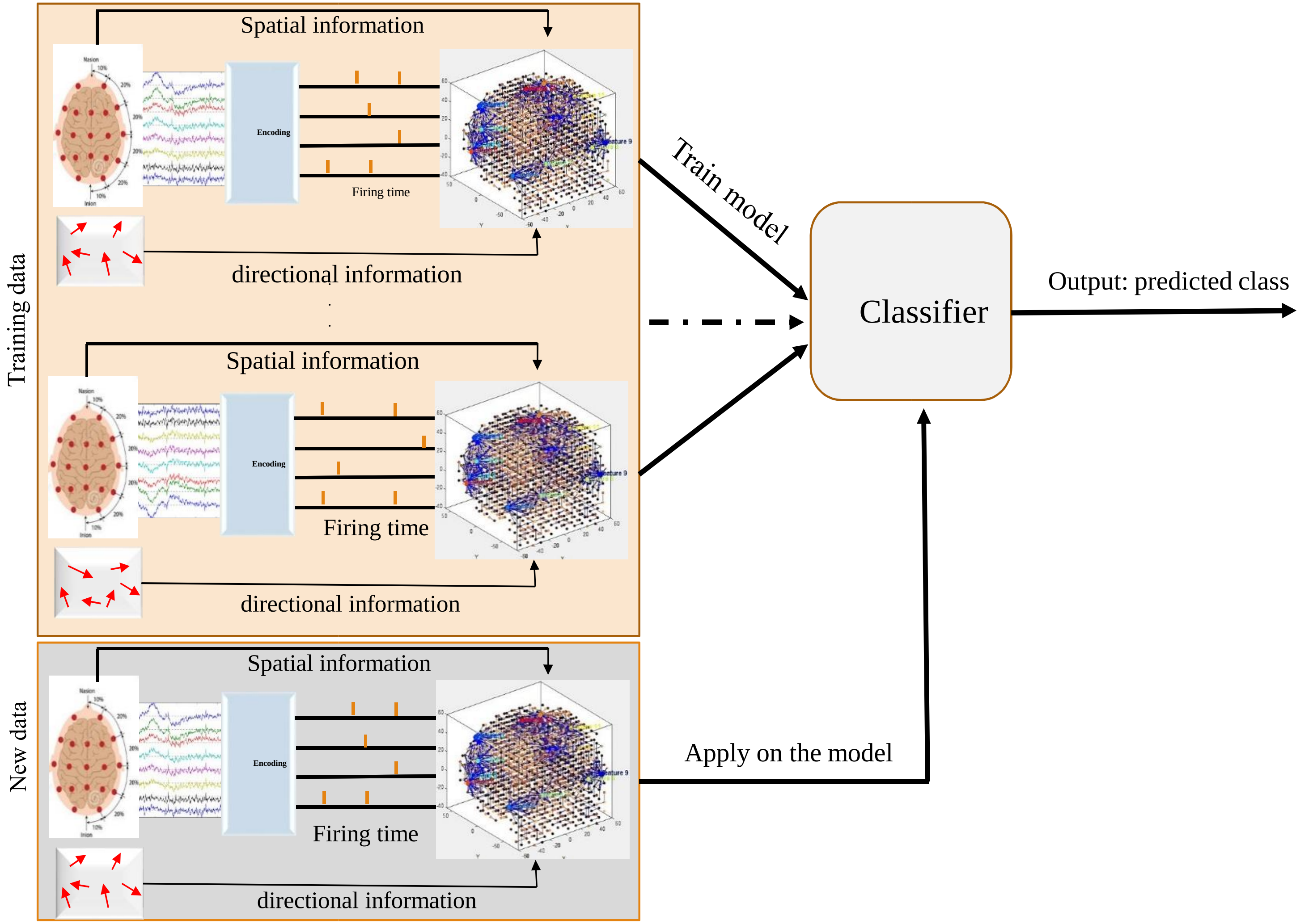
* K.Kumarasinghe, N.Kasabov, D.Taylor, Deep Learning and Deep Knowledge Representation in Spiking Neural Networks for Brain-Computer Interfaces, Neural Networks, vol.121 (2020),169-185, doi: https://doi.org/10.1016/j.neunet.2019.08.029.

Integration of space-, time- and direction/orientation in SNN.

PM using both fMRI and DTI data

Case study on response of schizophrenic patients to clozapine

Sengupta, N., McNabb, C. B., Kasabov, N., & Russell, B. R. (2018). Integrating Space, Time, and Orientation in Spiking Neural Networks: A Case Study on Multimodal Brain Data Modelling. IEEE Transactions on Neural Networks and Learning Systems, 29(11). doi:10.1109/TNNLS.2018.2796023



3. Implementation of BI- SNN models

From von Neumann principles and Atanassov's ABC Machine to Neuromorphic Hardware

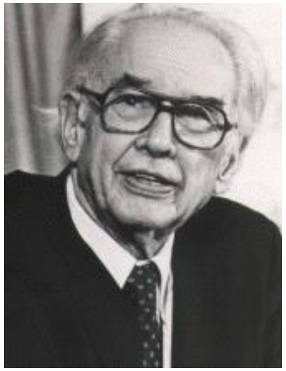
- The computer architecture of John von Neumann separates data and programmes (kept in the memory unit) from the computation (ALU); uses *bits*. First machine ABC by Atanassov and Berry.

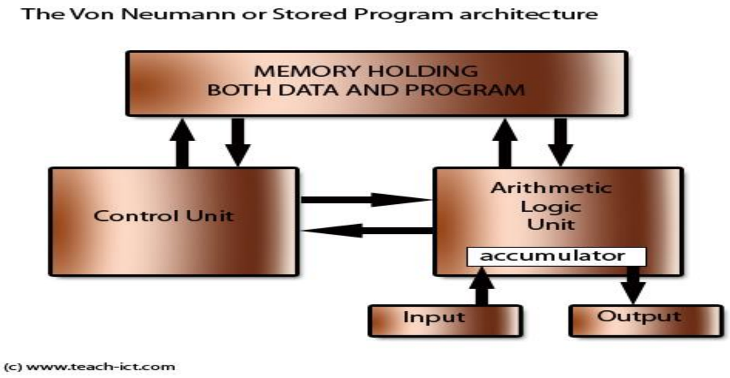
- A Neuromorphic architecture integrates the data, the programme and the computation in a SNN structure, similar to how the brain works; uses *spikes* (bits at times).

- A quantum computer uses *q-bits* (bits in a superposition) .

A SNN application system can be implemented using either of:

- von Neumann architecture;
- Neuromorphic architecture (BM TrueNorth, Manchester SpiNNaker; INI Zurich – Indiveri, Delbruck)
- Quantum computer (e.g. D-Wave).





N. Sengupta et al, (2018), From von Neumann architecture and Atanasoffs ABC to Neuromorphic Computation and Kasabov's NeuCube: Principles and Implementations, Chapter 1 in: Advances in Computational intelligence, Jotzov et al (eds) Springer 2018.

Neuromorphic hardware platforms

SpiNNaker (*Furber, S., To Build a Brain, IEEE Spectrum, vol.49, Number 8, 39-41, 2012).*

TrueNorth by IBM

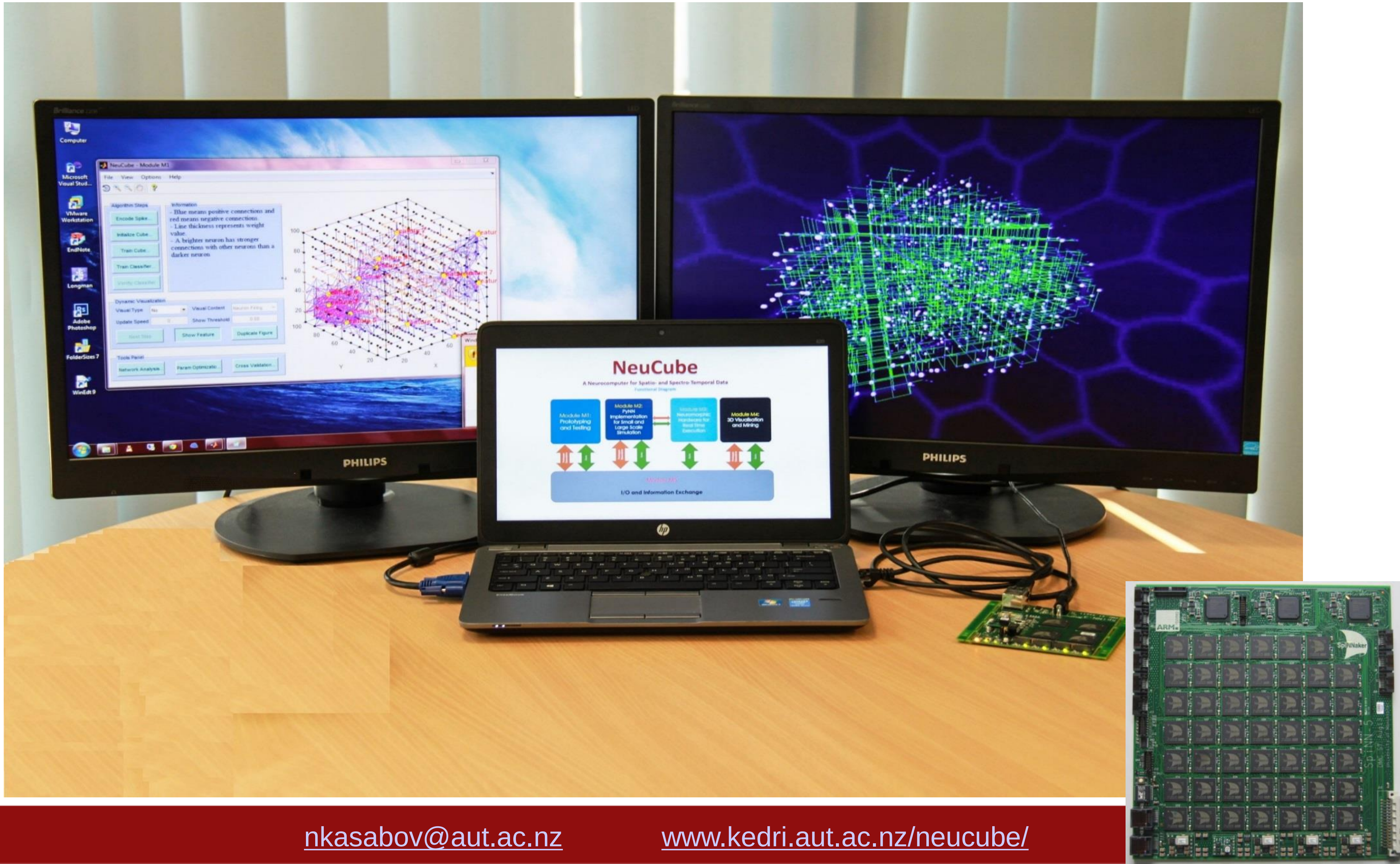
Silicon retina (the DVS) and silicon cochlea (ETH, Zurich, Toby Delbruck)) for input data encoding

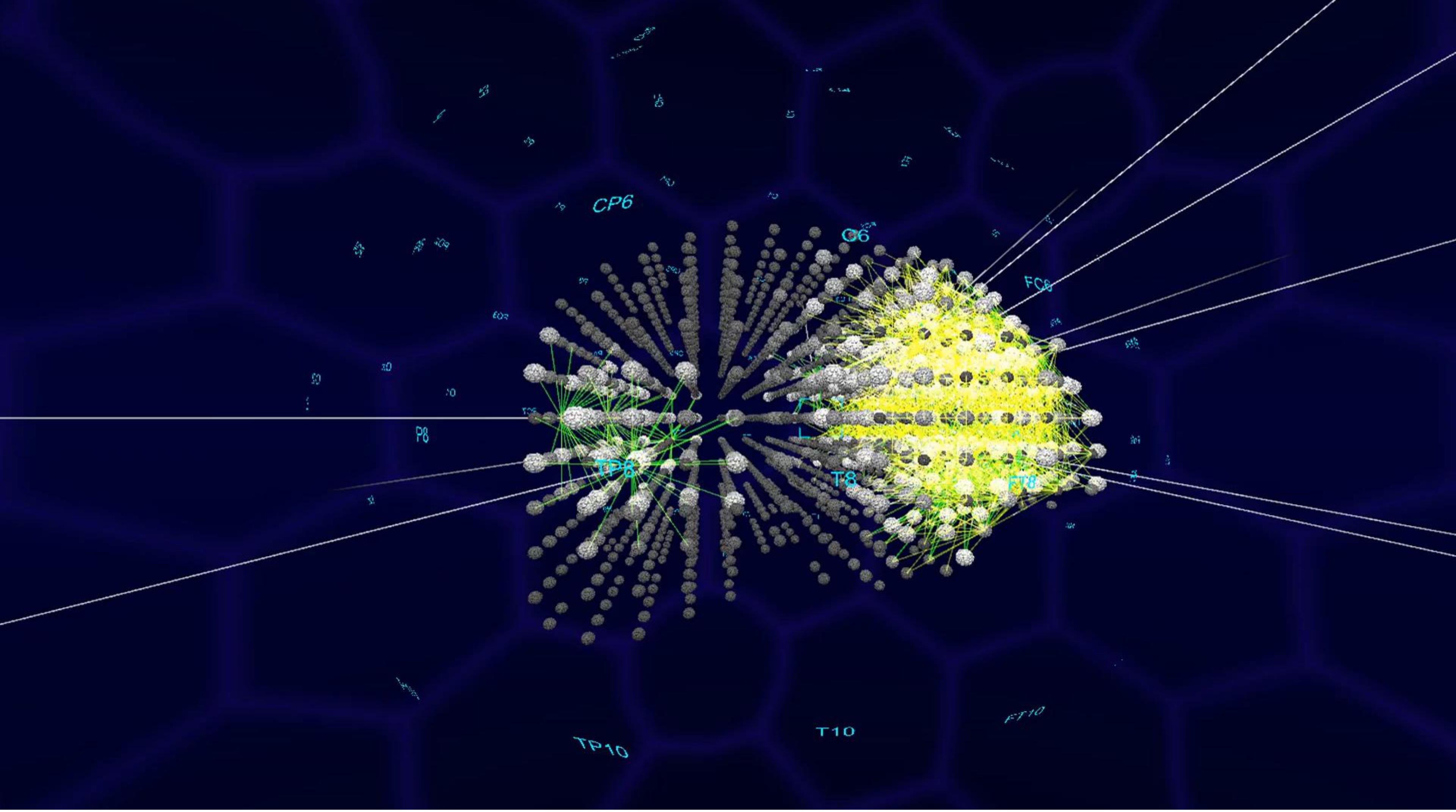
Loihi chip of Intel

S.Dey, A.Dimirov, Mapping and Validating a Point Neuron Model on Intel's Neuromorphic Hardware Loihi, Front.Neurosci, 2022

High speed and low power consumption!

NeuCube development environment for SNN system design for STD





N. Kasabov, N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli,R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube neuromorphic framework, Neural Networks, v.78, 1-14, 2016. http://dx.doi.org/10.1016/j.neunet.2015.09.011.

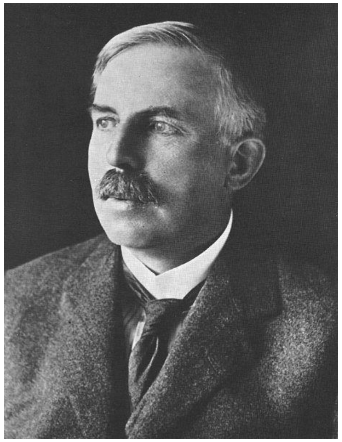
Quantum (or quantum inspired) computation

Quantum information principles: superposition; entanglement, interference, parallelism (M.Planck, A.Einstein, Niels Bohr, W.Heisenberg, John von Neumann, **E. Rutherford**)

- *Quantum bits (qu-bits)*

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

$$|\alpha|^2 + |\beta|^2 = 1$$



Ernest Rutherford (1871-1937)

- *Quantum vectors (qu-vectors)*

$$\left[\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m \end{array}\right]$$

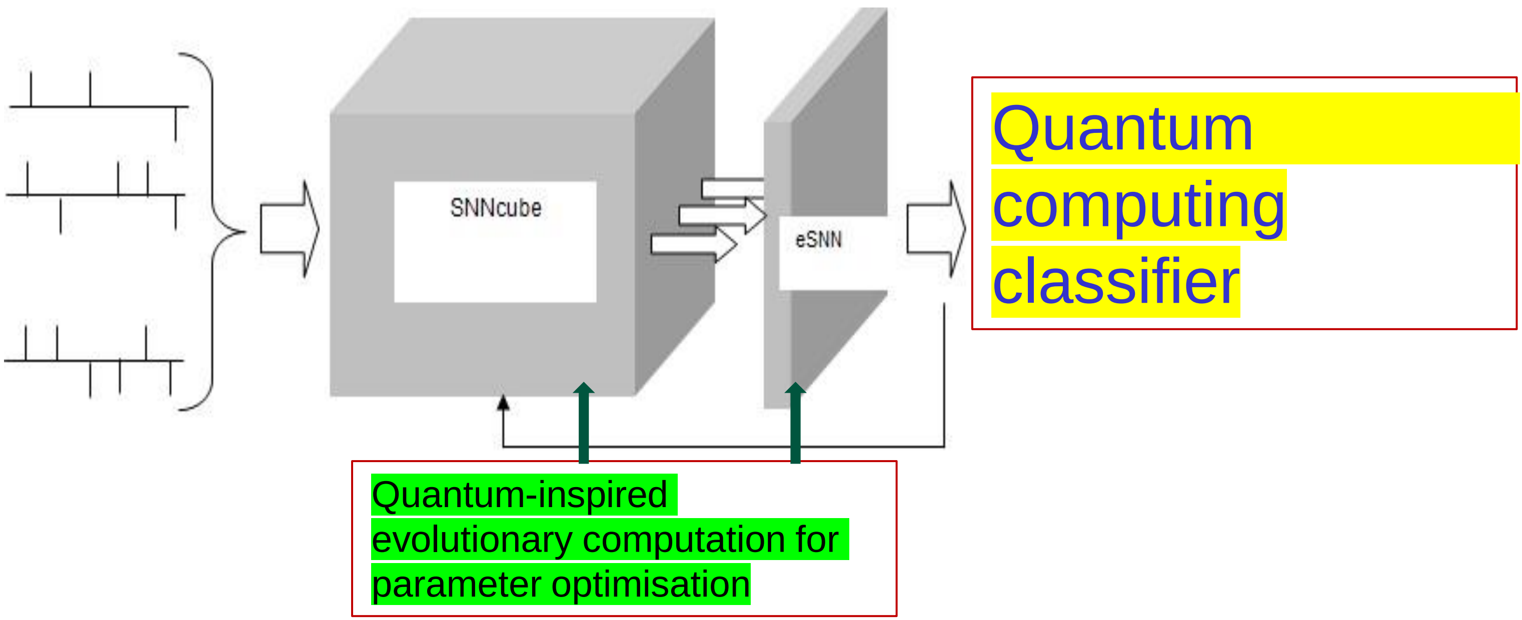
- *Quantum gates*

$$\begin{bmatrix} \alpha_i^j(t+1) \\ \beta_i^j(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_i^j(t) \\ \beta_i^j(t) \end{bmatrix}$$

- **Applications:**
  - Specific algorithms with polynomial time complexity for NP-complete problems (e.g. factorising large numbers, Shor, 1997; cryptography)
  - Search algorithms (Grover, 1996), $O(N^{1/2})$ vs $O(N)$ complexity)
  - Quantum associative memories

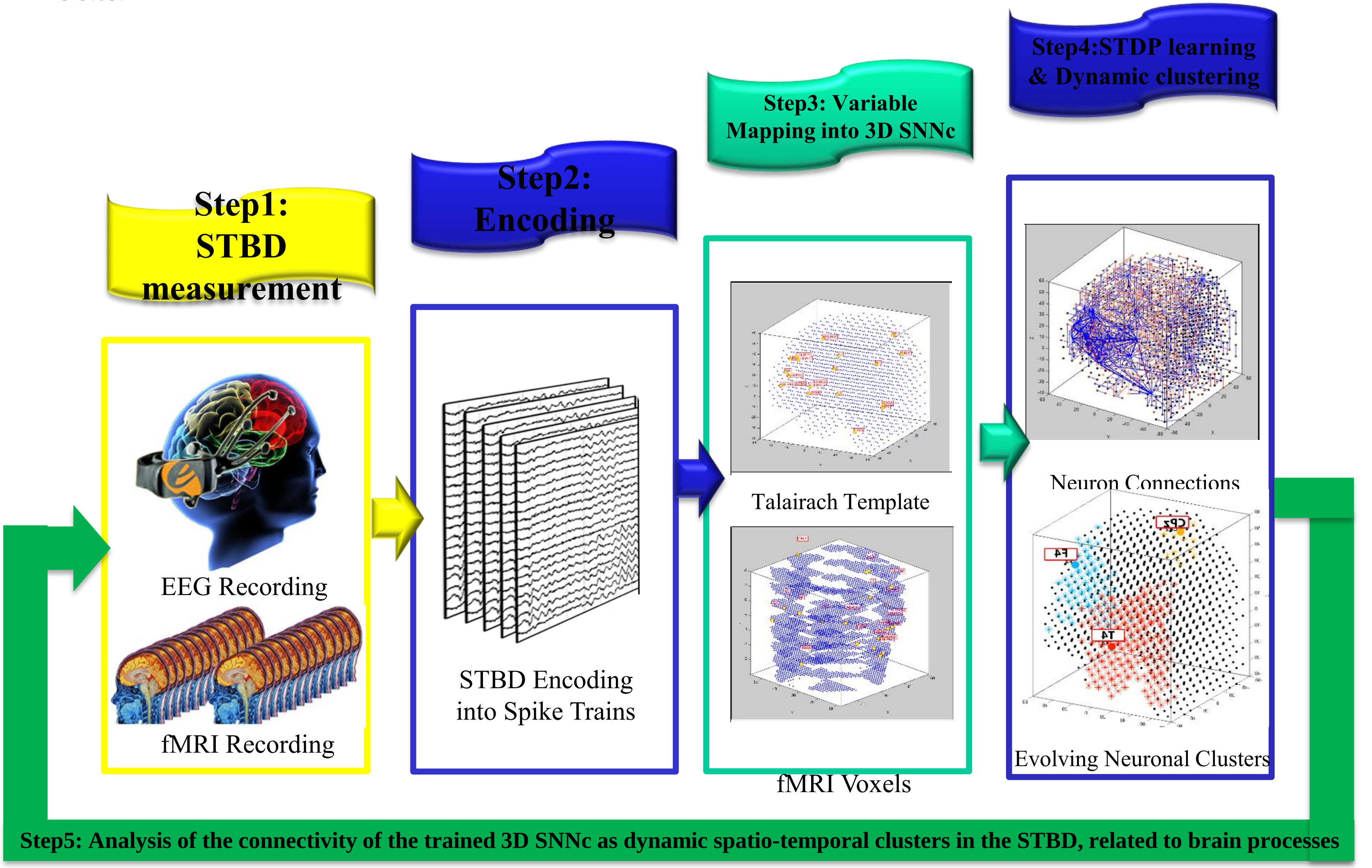
Quantum-enhanced neurocomputation architectures

Ravi, Jha, N. Kasabov, S.Bhattacharya, D.Coyle, G.Prasad (2023). From Quantum Computing to Quantum-inspired Computation for Neuromorphic Advancement – A Survey. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.24053250.v1



4. Application specific methods and systems based on BI-SNN

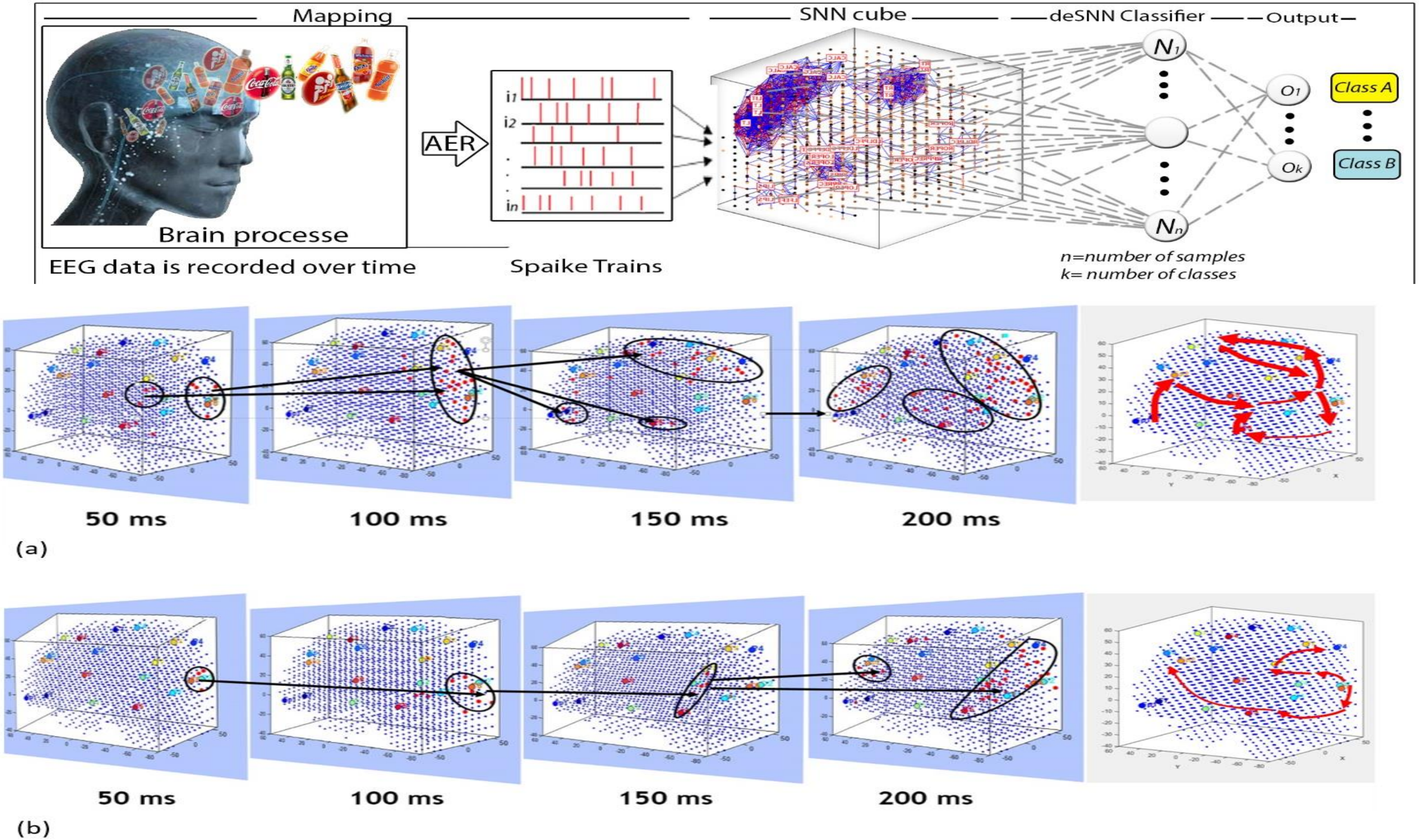
Deep learning and deep knowledge representation of neuroimaging spatio-temporal brain data



*Z.*Doborjeh, N. Kasabov, M. Doborjeh & Alexander Sumich**,** Modelling Peri-Perceptual Brain Processes in a Deep Learning Spiking Neural Network Architecture, ***Nature,*** Scientific REPORTS | (2018) 8:8912 | DOI:10.1038/s41598-018-27169-8; https://www.nature.com/articles/s41598-018-27169-8

Understanding human decision making. Detecting concealed information.

Modelling brain activities using EEG data and NeuCube

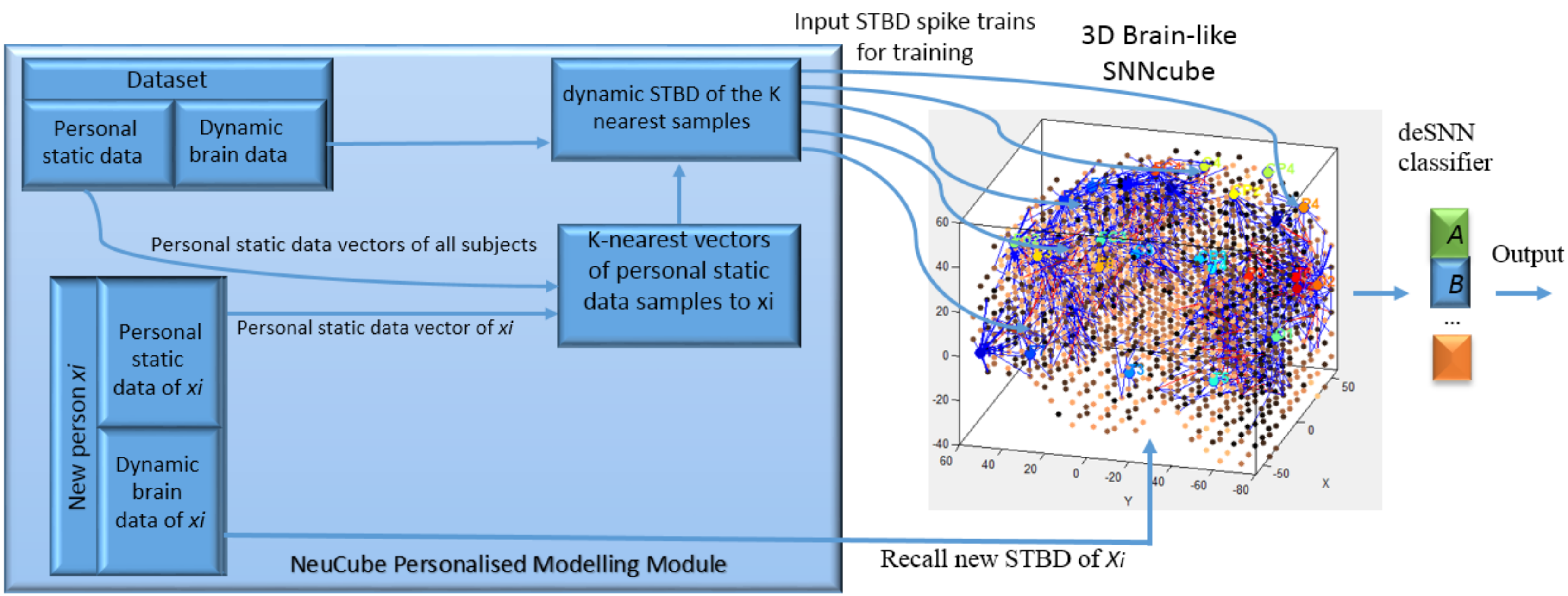


*Z.*Doborjeh, N. Kasabov, M. Doborjeh & Alexander Sumich**,** Modelling Peri-Perceptual Brain Processes in a Deep Learning Spiking Neural Network Architecture, ***Nature,*** Scientific REPORTS | (2018) 8:8912 | DOI:10.1038/s41598-018-27169-8; https://www.nature.com/articles/s41598-018-27169-8 (top 100 papers in 2018)

Predicting response to treatment of drug addicts
(Class M - who take medication; class OP – who do not take medication)

Doborjeh, M., and Kasabov, N., IEEE WCCI/IJCNN, 2016 (Response to treatment of drug addicts using clinical and EEG data)

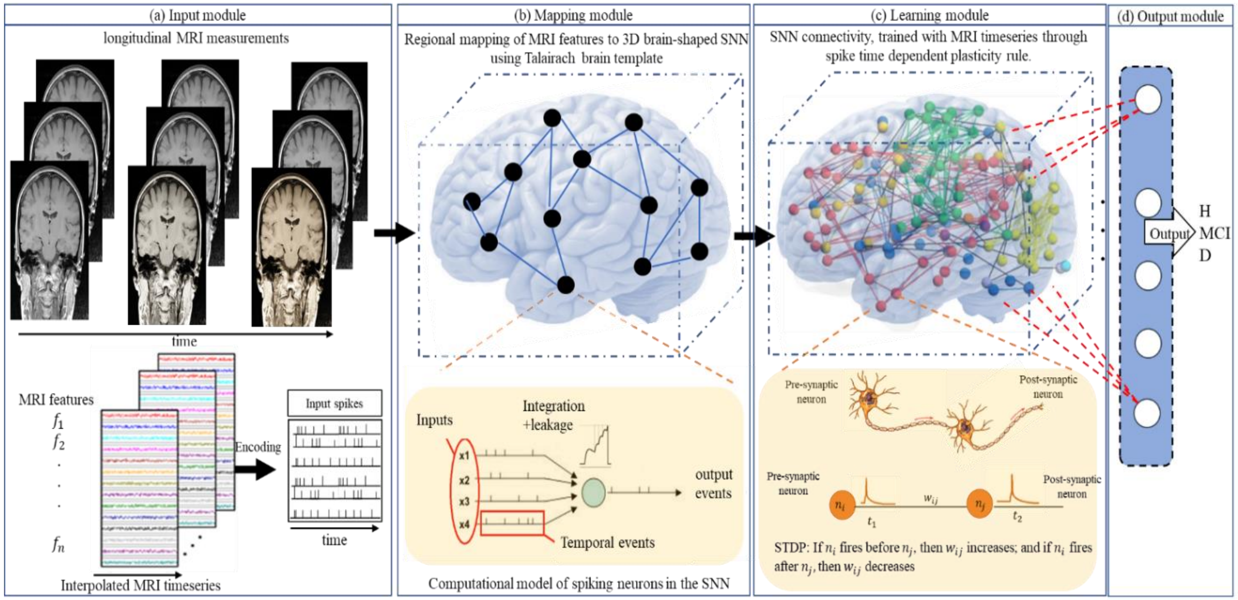
M. Doborjeh, N. Kasabov, Z. Doborjeh, R. Enayatollahi, E. Tu, A. H. Gandomi, Personalised modelling with spiking neural networks integrating temporal and static information, Neural Networks, 119 (2019),162-177.



Methods	NeuCube-Personalised modelling	NeuCube- Global modelling
Classification accuracy of class M versus class OP in %	Averaged over 47 trained PSNN models: 93.61	One trained SNN model using all subjects and tested via leave-one-out method: 79.00

Personalised prediction of dementia using longitudinal MRI data and NeuCube based on ESTAM

M. Doborjeh, Z.Doborjeh, A.Merkin, H.Bahrami, A.Sumich, R.Krishnamurthi, O. Medvedev, M.Crook-Rumsey, C. Morgan, I.Kirk, P.Sachdev, H. Brodaty, K. Kang, W.Wen, V. Feigin, N. Kasabov, Personalised Predictive Modelling with Spiking Neural Networks of Longitudinal MRI Neuroimaging Cohort and the Case Study ofr Dementia, Neural Networks, vol.144, Dec.2021, 522-539, https://doi.org/10.1016/j.neunet.2021.09.013,

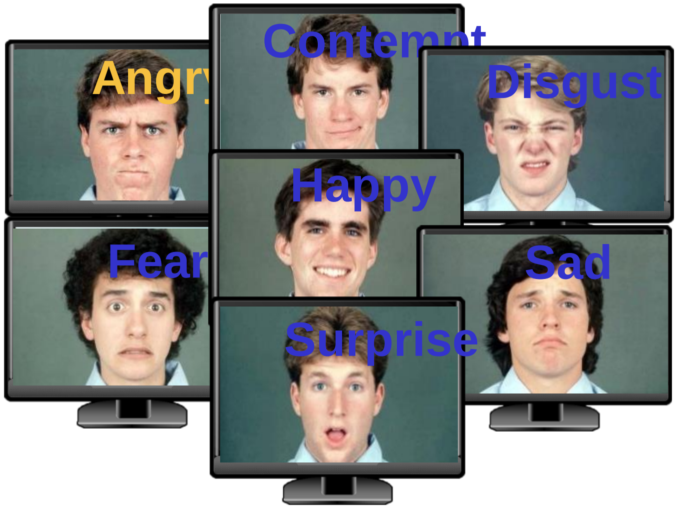


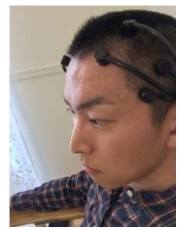
	BiLSTM Accuracy	BiLSTM F-Score	NeuCube Accuracy	NeuCube F-Score
Classification	43%	56%	95%	94%
2-year ahead prediction	40%	40%	91%	89%
4-year ahead prediction	41%	46%	73%	67%

Emotional facial expression recognition and facial expression production

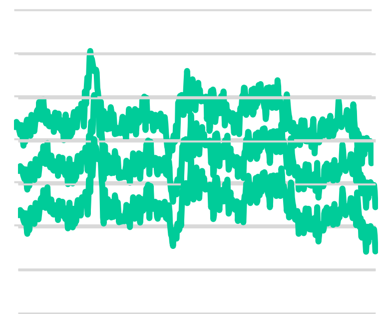
(H.Kawano, Z.Doborjeh, N.Kasabov, Proc. ICONIP 2016, Kyoto, 2016)

Facial Expression Perception Task

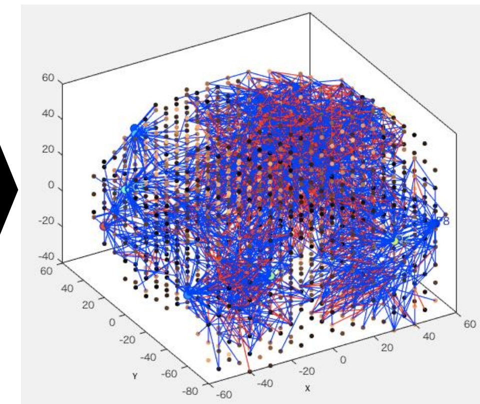




14ch EEG



94.3 %

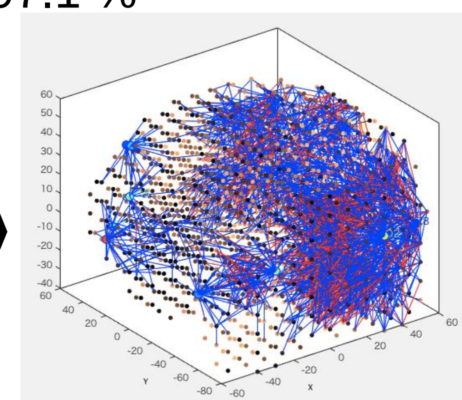


Face Expression Production Task

14ch EEG

97.1 %

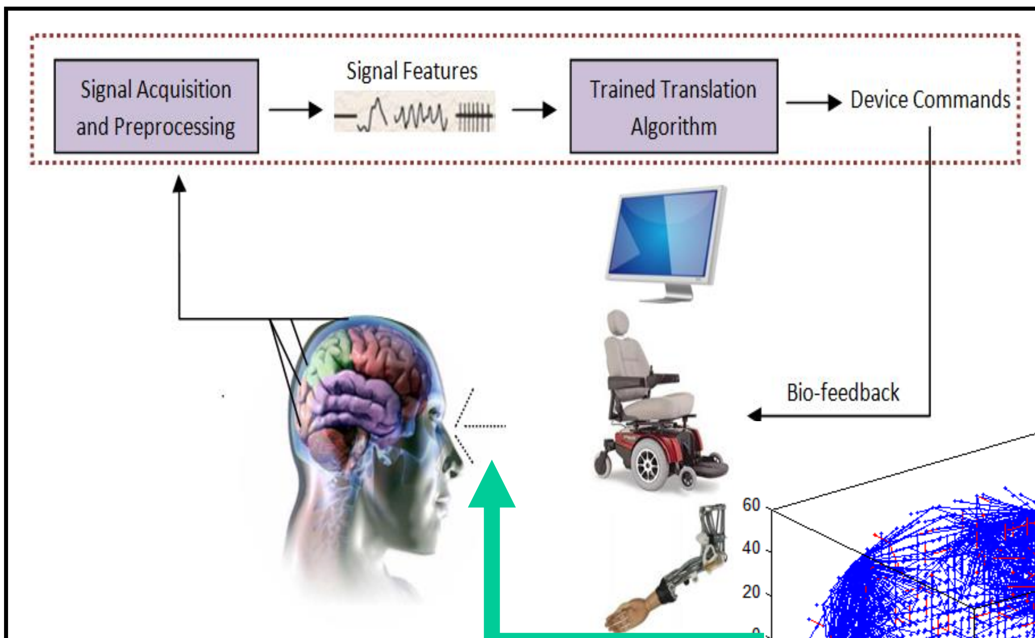
NeuCube

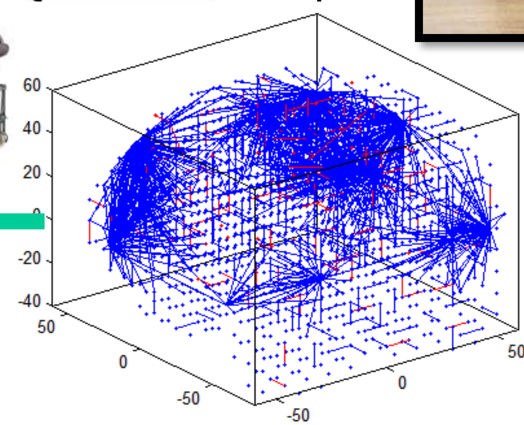


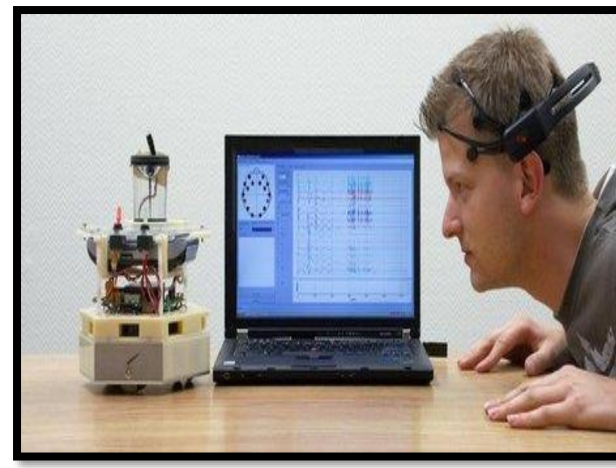
Brain Machine Interfaces using Brain-Inspired SNN

Brain-Computer Interfaces (BCIs) are systems trained on human brain data (e.g. EEG) for humans to communicate directly with computers or external devices through their brains

BI-BCI are designed using a brain template.







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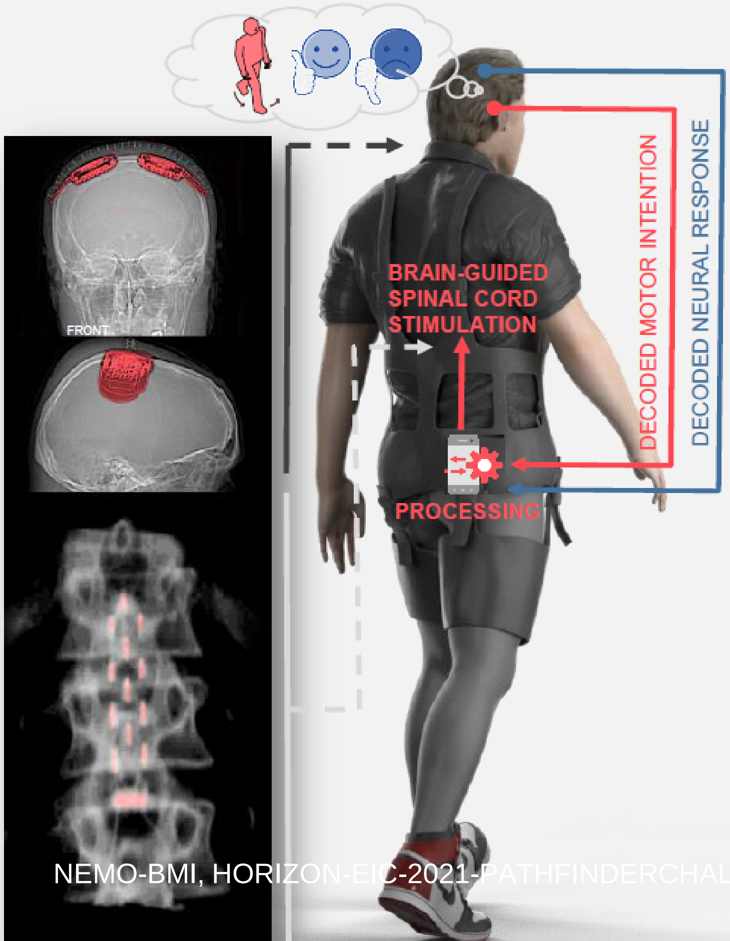
NEMO-BMI

Adaptive decoding brain signals predict movements and spinal cord stimulation

https://nemo-bmi.net/

Fully embedded auto-adaptive Brain Machine Interface



Implantable measure – stimulation technology

- Chronic wireless brain recording WIMAGINE implant
- Spinal cord stimulation ONWARD implant
- 2 Clinical trials ongoing: Brain machine interface proof of concept

Auto-adaptive motor BMI decoding

IICT-BAS

- Natural control based on patient's intention
- Multiple degrees of freedom control
- Decoding of Neural response linked to intention/action coherence
- Real-time auto-adaptive decoder
- Assistance free
- Neuromorphic decoding algorithms

Brain-guided spinal cord Stimulation

- Epidural Electrical Targeted dynamic stimulation
- Auto-adaptative stimulation Patterns

Miniaturization of BMI technology

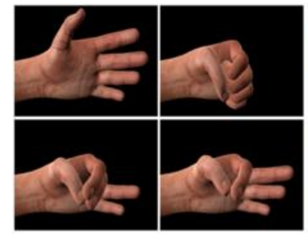
- Low power integrated circuit for accelerating the decoding algorithms
- High system level integration
- Portable battery-powered solution

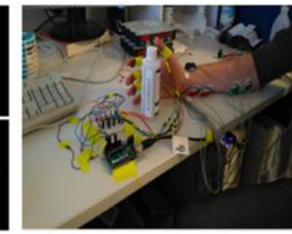
NEMO-BMI, HORIZON-EIC-2021-PATHFINDERCHALLENGES-01-... Swiss, Bulgari

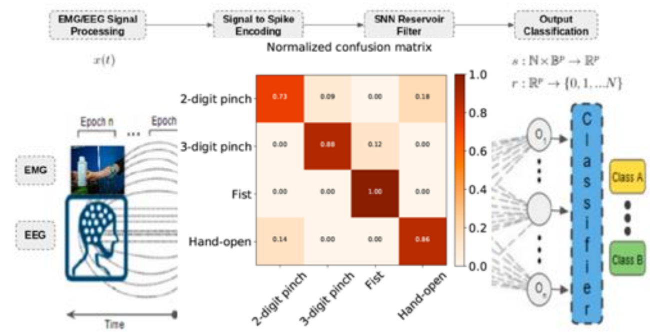
Horizon Europe: CEA France, EPFL Switzerland, ONWARD The Netherlands, IICT BAS Bulgaria

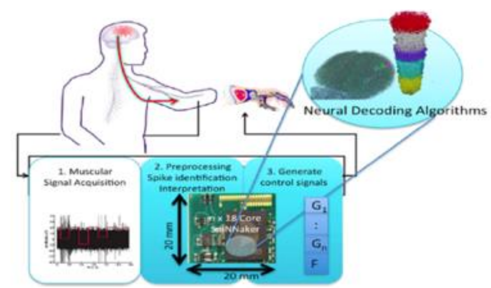
NeuCube on SpiNNaker to predict hand movement for a prosthetic hand: Muscle cells and brain neurons form ESTAM

- Classification of electrical signals
  - real-time control of active prosthetics
  - low power
- Record electrical activity of participants during prescribed hand movements
- Classification with reservoir of spiking neurons
  - encode signals into spikes
  - train network (unsupervised)
  - readout to classify





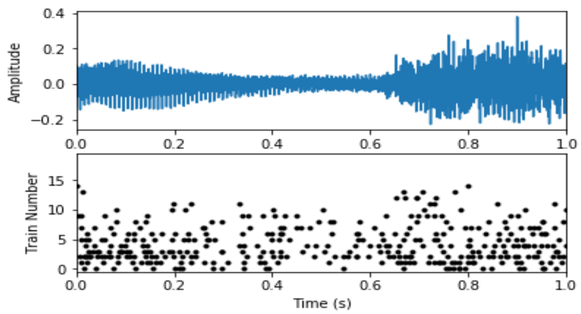


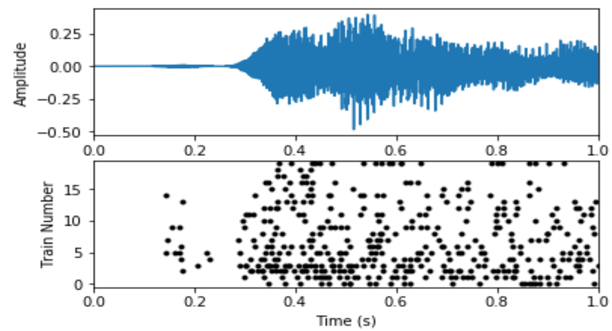


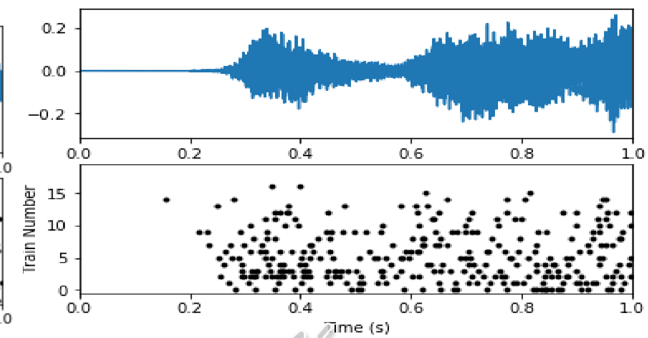
Behrenbeck, Z. Tayeb, C. Bhiri, C. Richter, O. Rhodes, N. Kasabov,- J. Espinosa-Ramos, S. Furber, G. Cheng, and J. Conradt, “Classification and regression of spatio-temporal signals using neucube and its realization on spinnaker neuromorphic hardware,” Journal of Neural Engineering, vol. 16, no. 2, 2019,

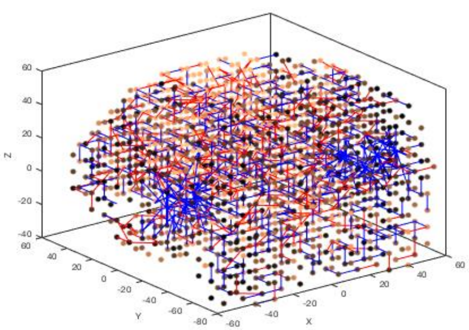
Deep learning and modelling of audio and visual and multimodal audio-visual data in BI-SNN

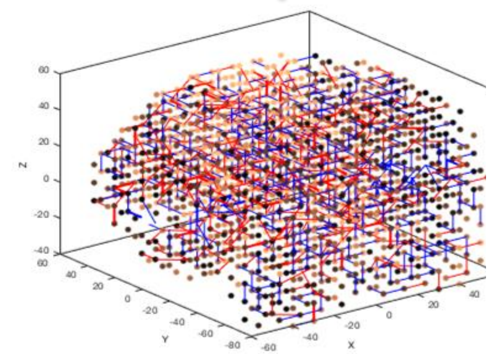
Using tonotopic, *stereo* mapping of sound and deep learning in NeuCube

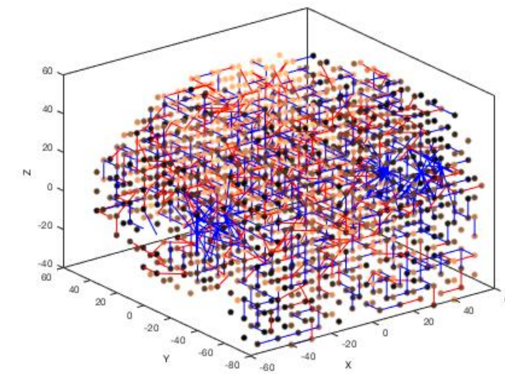












	Mozart	Bach	Vivaldi
Predicted 1	171	3	1
Predicted 2	9	176	1
Predicted 3	0	1	178

BI-SNN for predictive modelling of spatio-temporal streaming data

Examples:

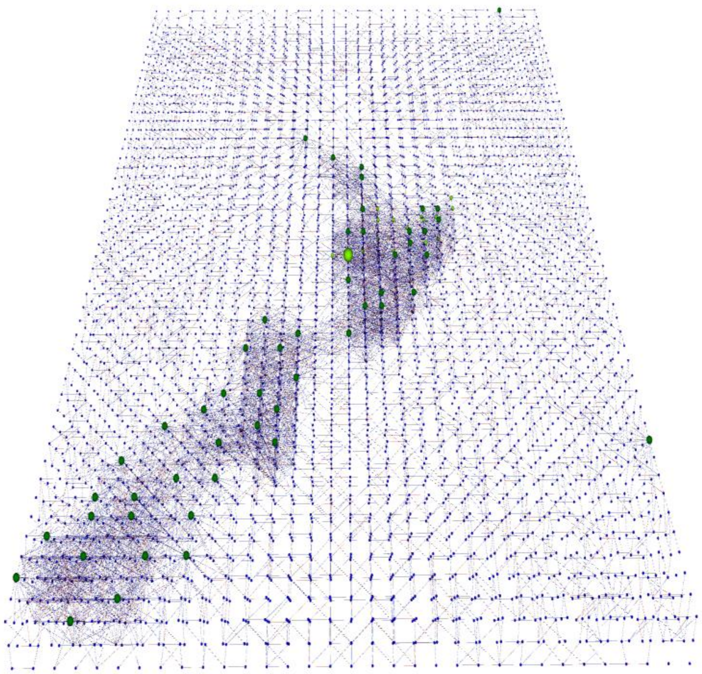
1) Environmental streaming data (e.g. predicting individual stroke)

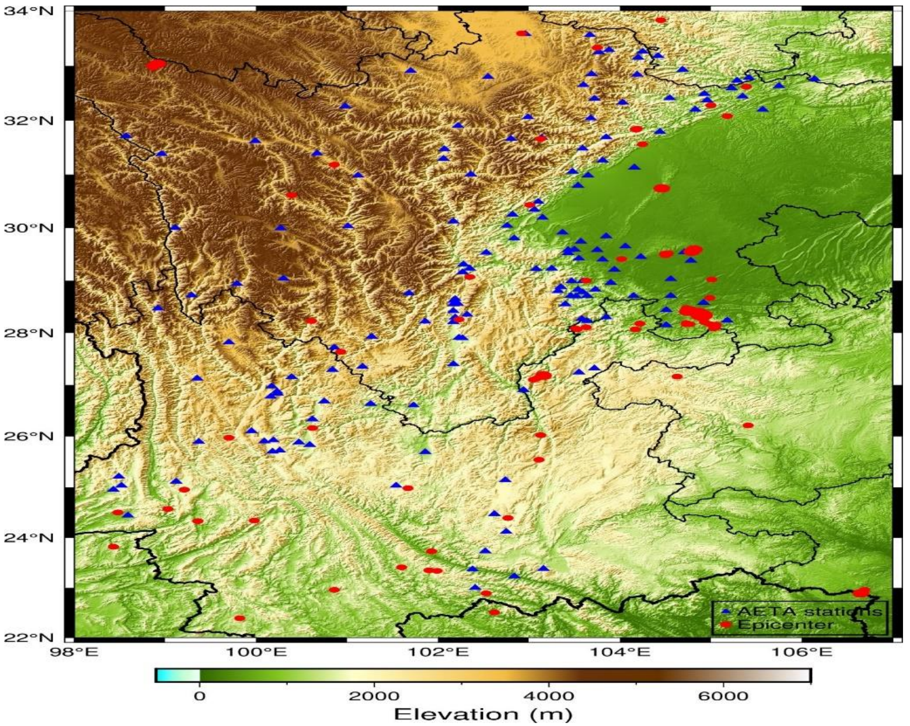
2) Moving object recognition

3) Multisensory systems for predicting pollution, floods, earthquakes

4) NeuCube modelling of the propagation of earthquakes through New Zealand.

5) Financial data predictive modelling

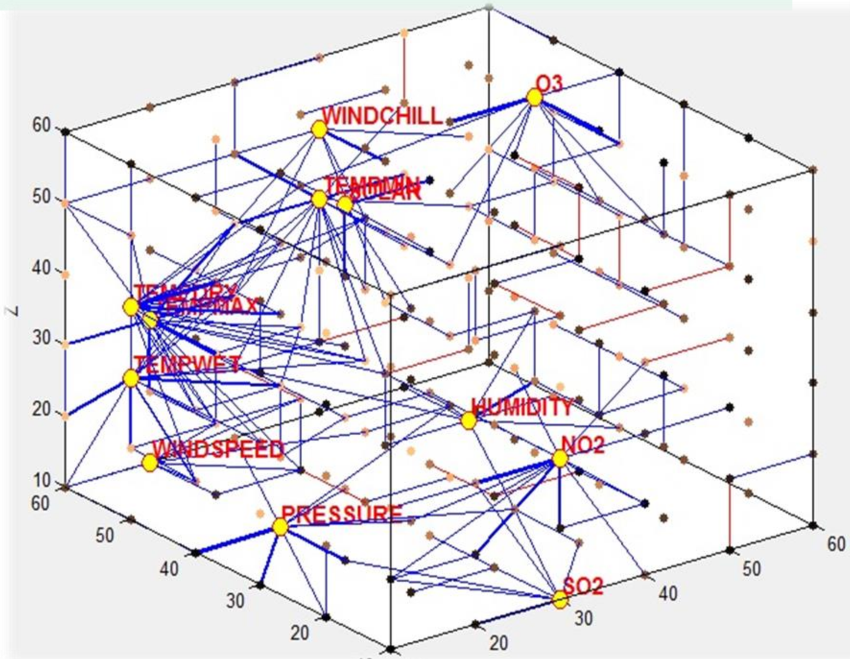


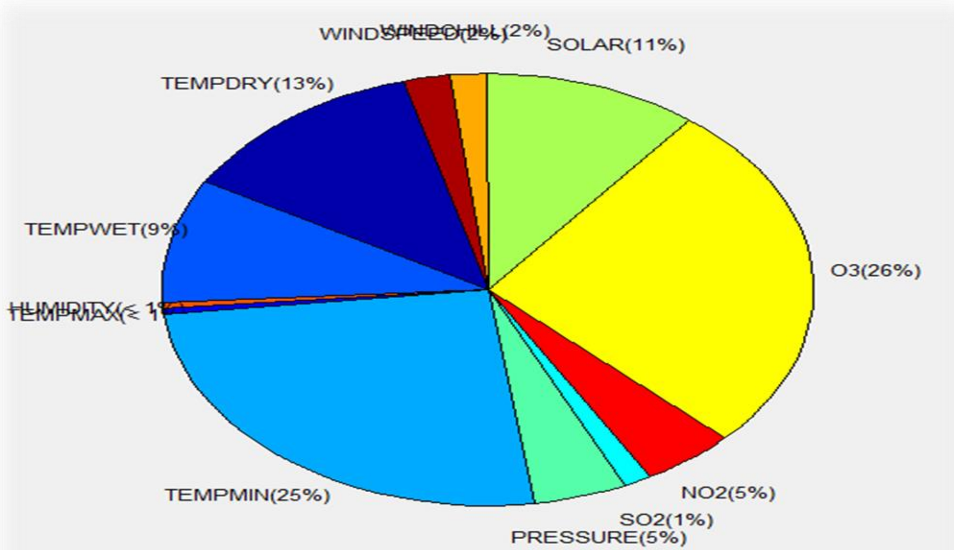


Personalised prediction of risk for stroke days ahead

(N.Kasabov, M. Othman, V.Feigin, R.Krishnamurti, Z Hou et al - Neurocomputing 2014)

METHODS	SVM	MLP	KNN	WKNN	NEUCUBE[ST]
1 day earlier (%)	55 *(70,40)*	30 *(50,10)*	40 *(50,30)*	50 *(70,30)*	**95** ***(90,100)***
6 days earlier (%)	50 *(70,30)*	25 *(20,30)*	40 *(60,20)*	40 *(60,20)*	**70** ***(70,70)***
11 days earlier (%)	50 *(50,50)*	25 *(30, 20)*	45 *(60,30)*	45 *(60,30)*	**70** ***(70,70)***





(d) Neuron proportion based on spike transmission

- SNN achieve better accuracy
- SNN predict stroke much earlier than other methods
- New information found about the predictive relationship of variables

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Personalised predictive modelling of individual risk of stroke

How environmental risk factors can influence the risk of individual stroke occurrence?

>1200 individuals

Stroke (2011-2012)

Clinical records (37 variables)

Affected group of 169 individuals: (45% female); 55% male; mean-age= 74.05> mean-age non-affected group (70.4); had *history of stroke* in close family member, *overweight*, *older*, *smokers*, *diabetic*, and taking *medication*.

10 environmental (CO, NO2, O3, SO2, and PM10, PM2.5, temperature, wind-direction average, wind-speed, and solar radiation).

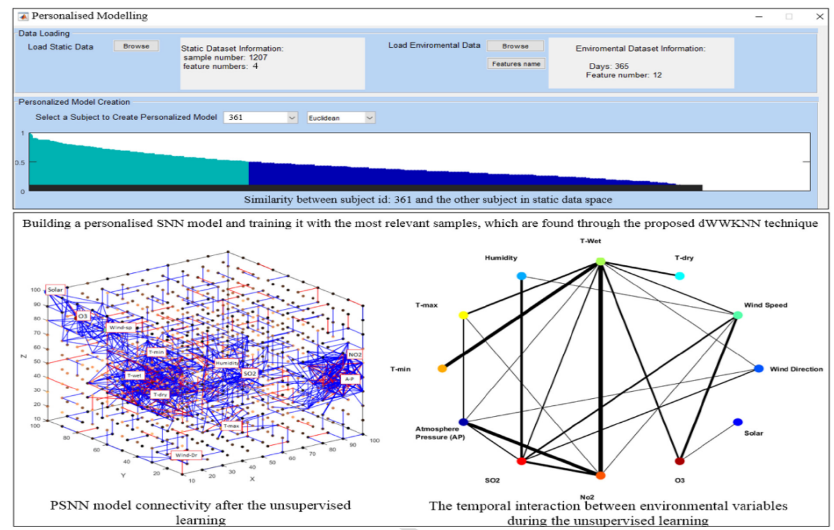


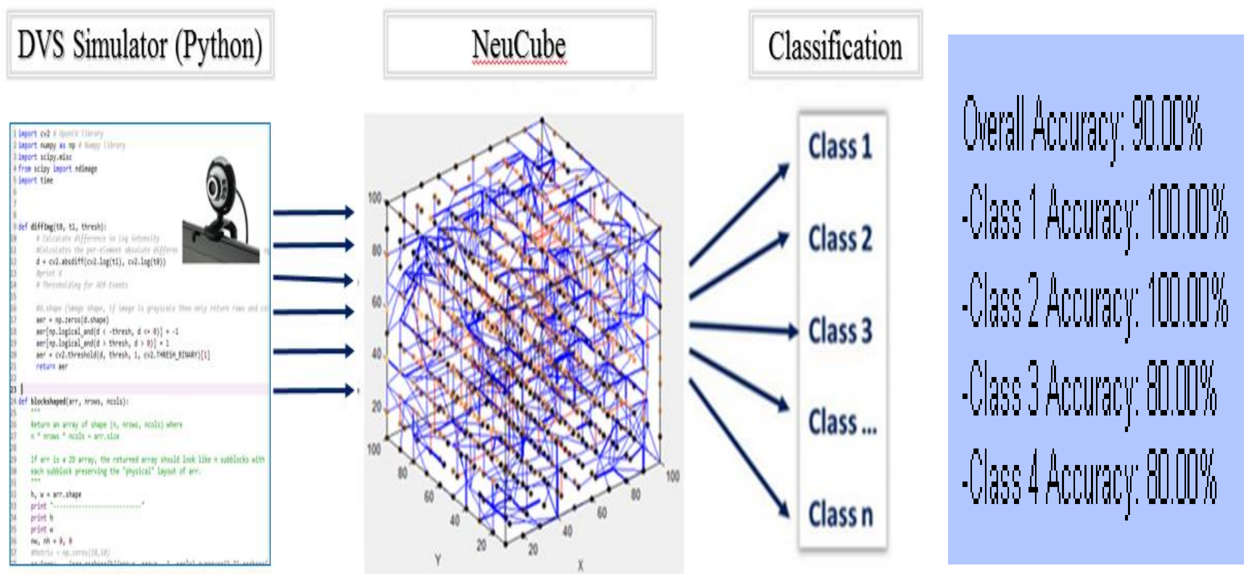
Fig. 9. The user interface of the proposed personalised predictive system for prediction of risk of stroke. A PSNN model is created to spatially map the environmental variables, where the most correlated variables are mapped to closer input neurons. Then the PSNN model was trained on the temporal spike sequences using STDP unsupervised learning to adapt the model connections. Blue lines represent excitatory synapses (positive connections), whereas red lines refer to inhibitory synapses (negative connections). In the graph, the amount of spike communication between clusters of neurons, centred by input variables, is captured as the thickness of lines. The thicker the line, the more interactions between variables during STDP learning.

Maryam Doborjeh, Zohreh Doborjeh, Alexander Merkin, Rita Krishnamurthi, Reza Enayatollahi, Valery Feigin, **Nikola Kasabov**, Personalised Spiking Neural Network Models of Clinical and Environmental Factors to Predict Stroke, Cognitive Computation, COGN-D-20-00511R2, 26 , 2021, https://www.springer.com/journal/12559.

BI-SNN for fast object recognition from video streaming data

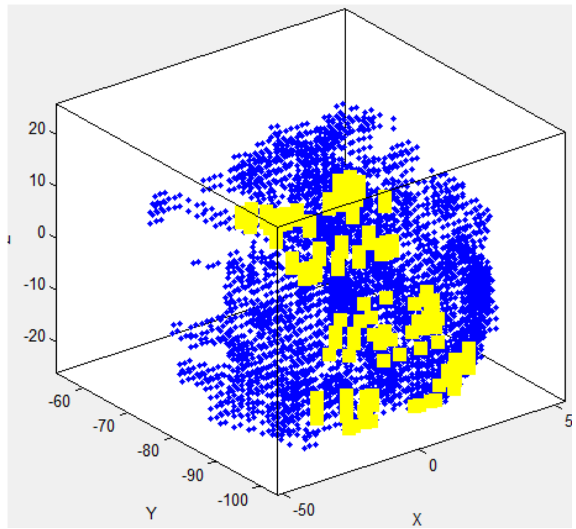
Applications:

- Surveillance systems
- Cybersecurity
- Military applications
- Autonomous vehicles

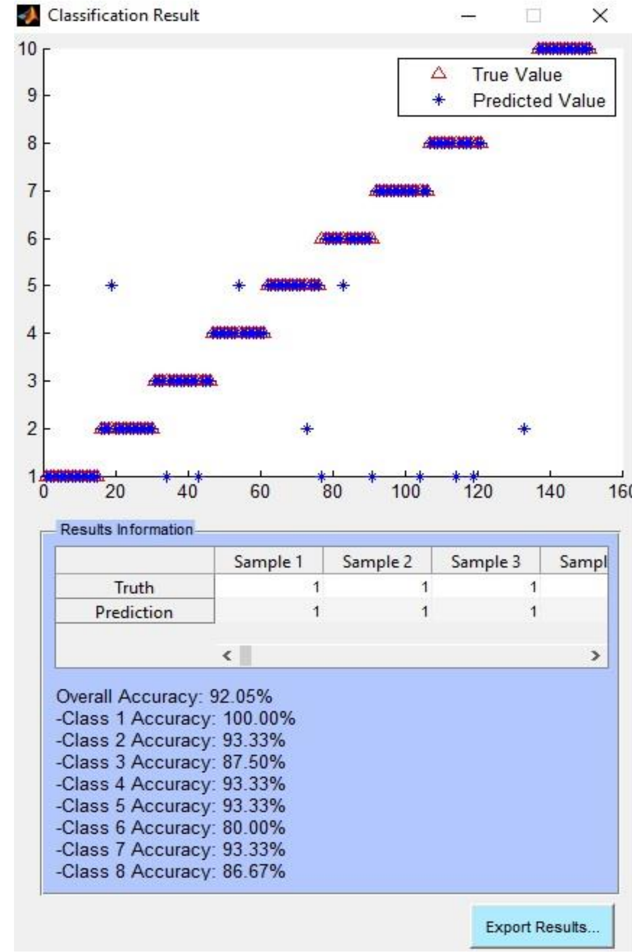


Deep learning and knowledge representation of moving objects using DVS and retinotopic mapping in NeuCube

30000 moving digits in 8 fonts and sizes from DVS MNIST



NeuCube with 4262 neurons from V1 and V2

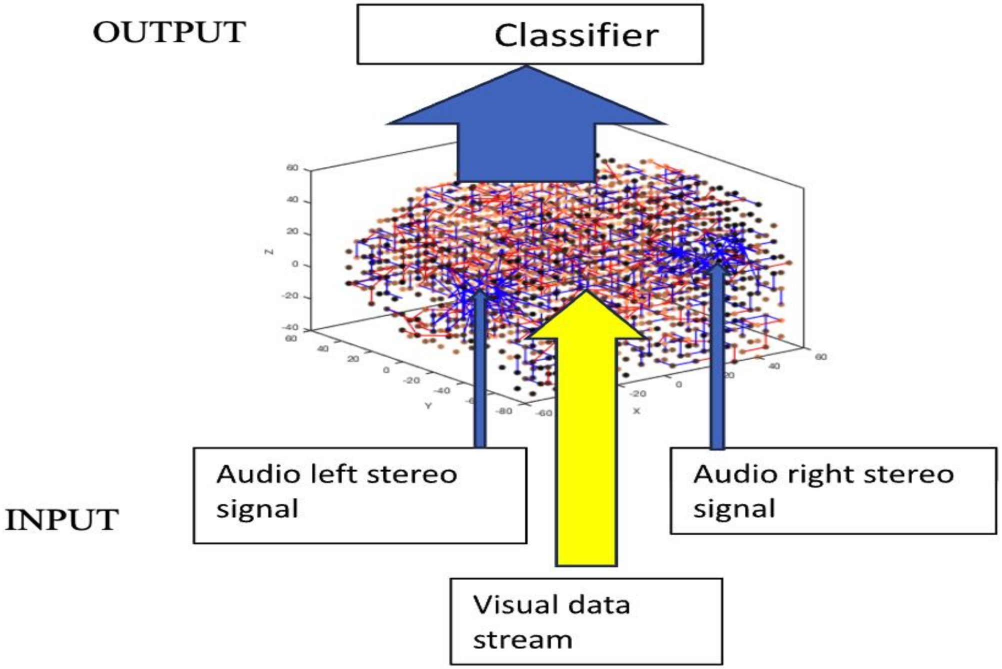


L.Paulin**,** A.Abbott, N.Kasabov, A retinotopic spiking neural network system for accurate recognition of moving objects using NeuCube and dynamic vision sensors, Frontiers of Comp. Neuroscience, 2018, doi:10.3389/fncom.2018.00042.

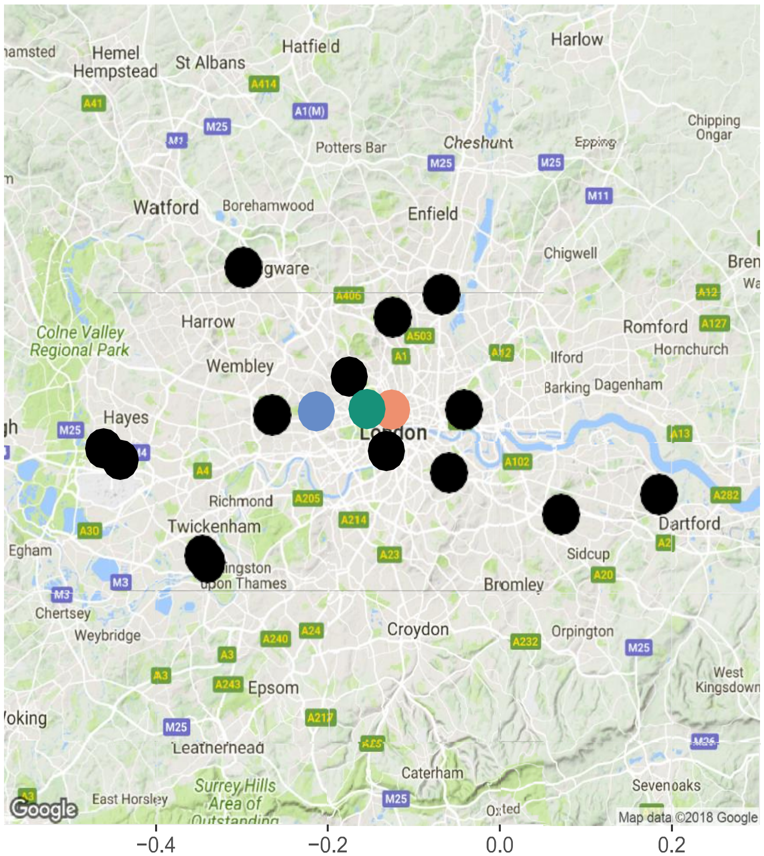
Multimodal audio-visual ESTAM for moving object recognition

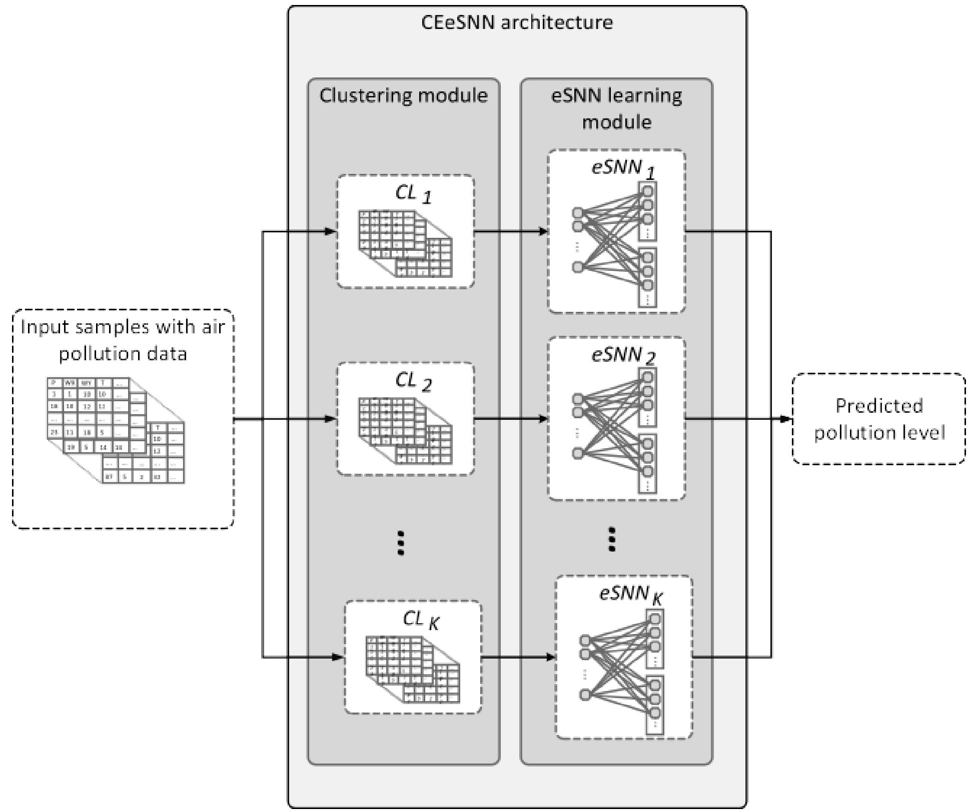
Kasabov, N., B.Bhattacharya, et al, AViAM-SNN: A Framework for Audio-Visual Associative Memories using Brain-inspired Spiking Neural Networks, Applied Soft Computing, 2024 (submitted)

- Training on both modalities
- Recall on only one modality
- Case studies on airplane and train recognition



Using an ensemble of eSNN for Predicting Hourly Air Pollution in London Area from sensory TSD

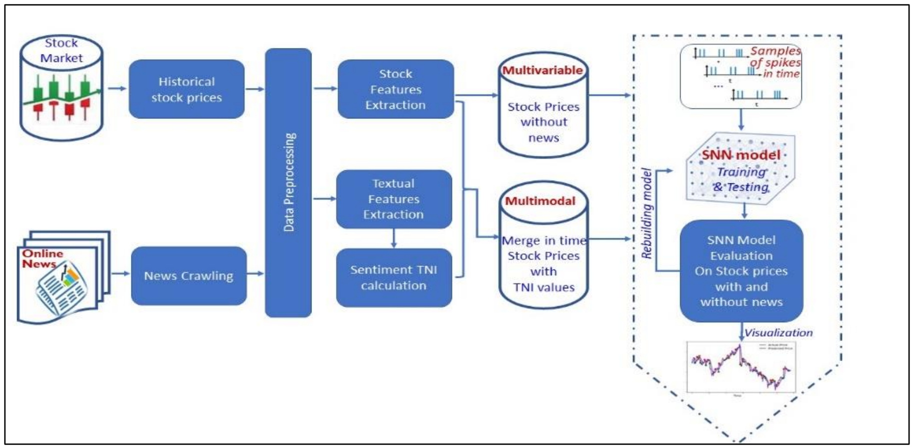


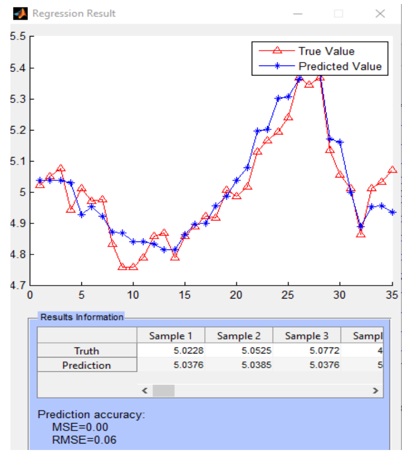


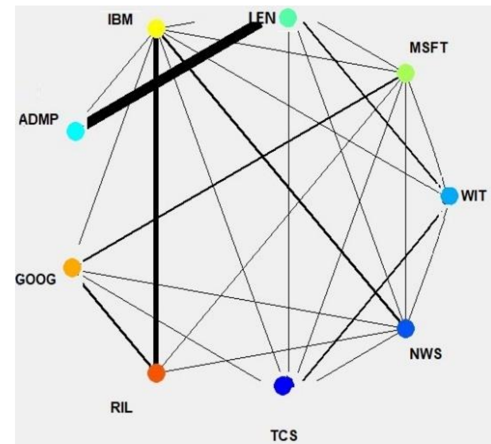
P. S. P Maciaga, N. K. Kasabov, M. Kryszkiewicza, R. Benbenik, Prediction of Hourly Air Pollution in London Area Using Evolving Spiking Neural Networks, Environmental Modelling and Software, Elsevier, vol.118, 262-280, 2019, https://www.sciencedirect.com/science/article/pii/S1364815218307448?dgcid=author

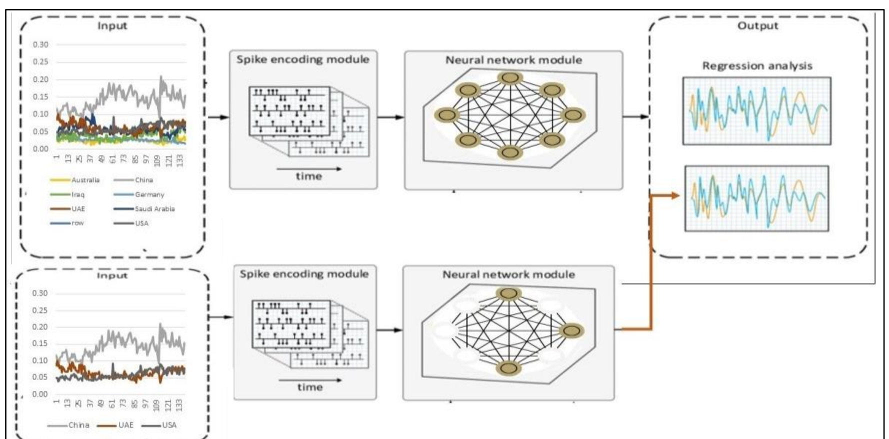
ESTAM for multimodal financial data prediction

I AbouHassan, N K Kasabov, VG.M. J P Kulkarni, Spiking neural networks for predictive and explainable modelling of multimodal streaming data on the Case Study of Financial Time Series Data and on-line news, Scientific Reports, November, 2023.









I. AbouHassan, N. Kasabov, T. Bankar, R. Garg, and B. S. Bhattacharya, "ePAMeT: Evolving predictive associative memory for time series based on spiking neural networks with case studies in economics and finance," TechRxiv, 9 2023, preprint. Online. Available: https://doi.org/10.36227/techrxiv.24063975.v1

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4. Discussions and future directions

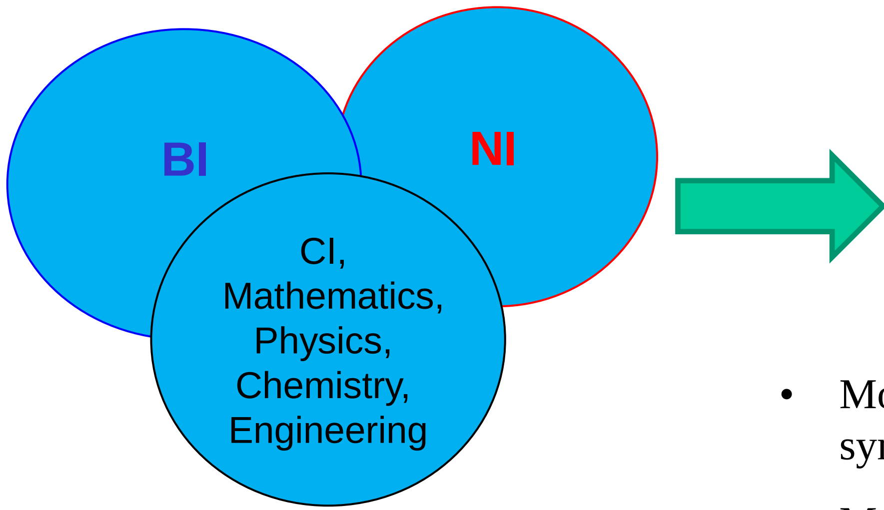
Advantages of BI-SNN:

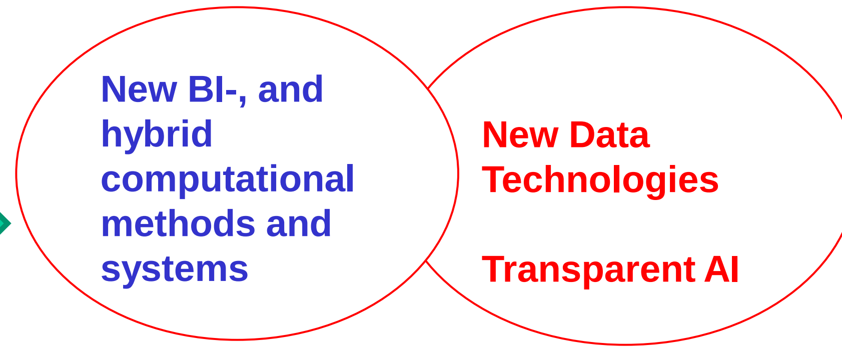
1. Self-organised, evolvable structure (no fixed number of layers/neurons, etc.)
2. *Event* based (asynchronous), fast, incremental, potentially "life-long" learning.
3. Temporal (spatio-temporal) associations learned.
4. Interpretability, e.g. TSK representation
5. Low computational power
6. Fault tolerance

Problems and limitations of BI-SNN

- Sensitive to parameter values
- Large number of parameters to be optimised
- No rigid theory yet.
- Ethical issues: www.mindthegap.ai

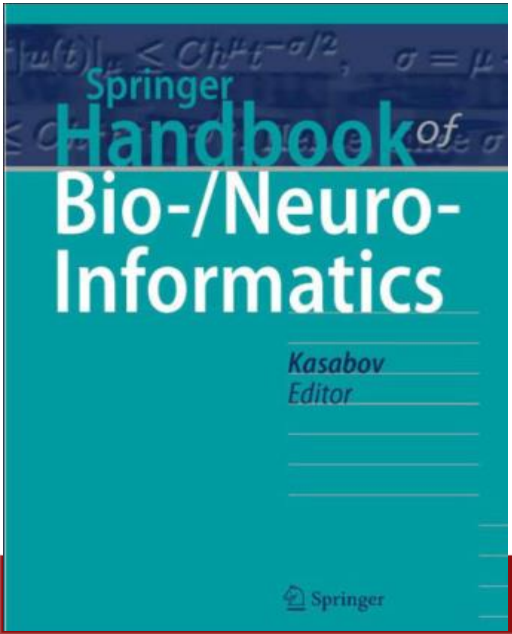
Future directions: BI-AI through BI-SNN architectures

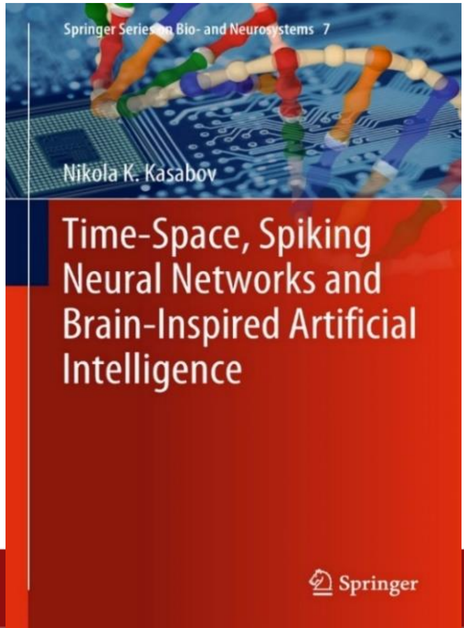




- Modelling emergence of symbolic representation
- Multimodal and multi-model SNN systems
- Quantum-inspired computation: Spikes as q-bits - in a superposition of 1/0

- Real time event prediction systems
- Embedded systems
- Mental health evaluation systems
- Neurological prosthetics
- Brain-inspired SNN for quantum comput



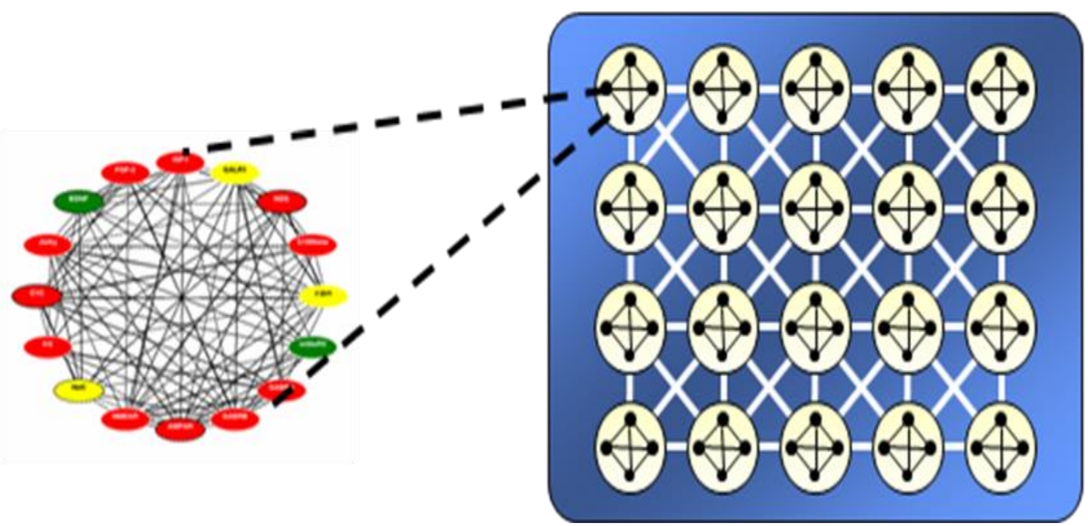


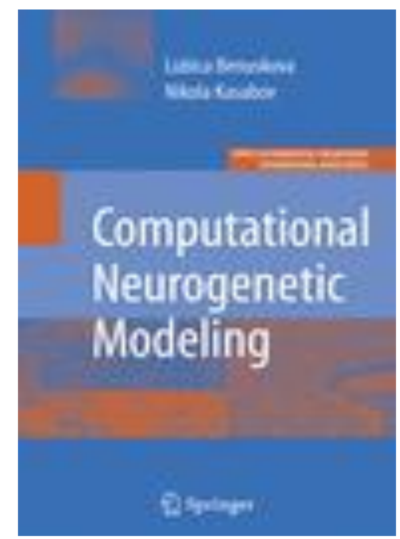
Future development:
Computational Neuro-Genetic Modelling (CNGM)

- Benuskova and Kasabov (2007)

SNN that incorporate a gene regulatory network (GRN) as a dynamic parameter systems to capture dynamic interaction of genes (parameters) related to neuronal activities of the SNN.

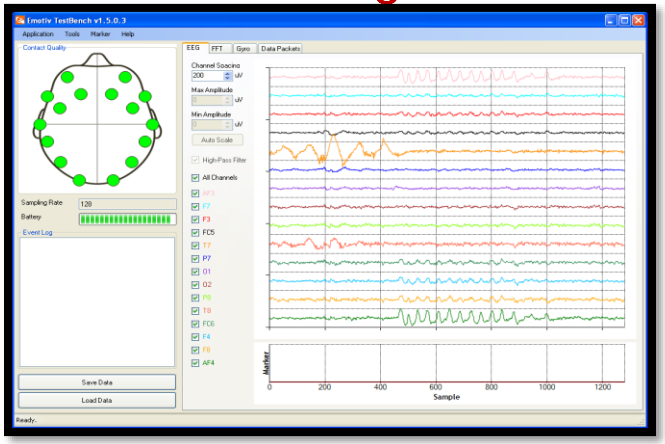
- Functions of neurons and neural networks are influenced by internal networks of interacting genes and proteins forming an abstract GRN model.
- The GRN and the SNN function at different time scales.



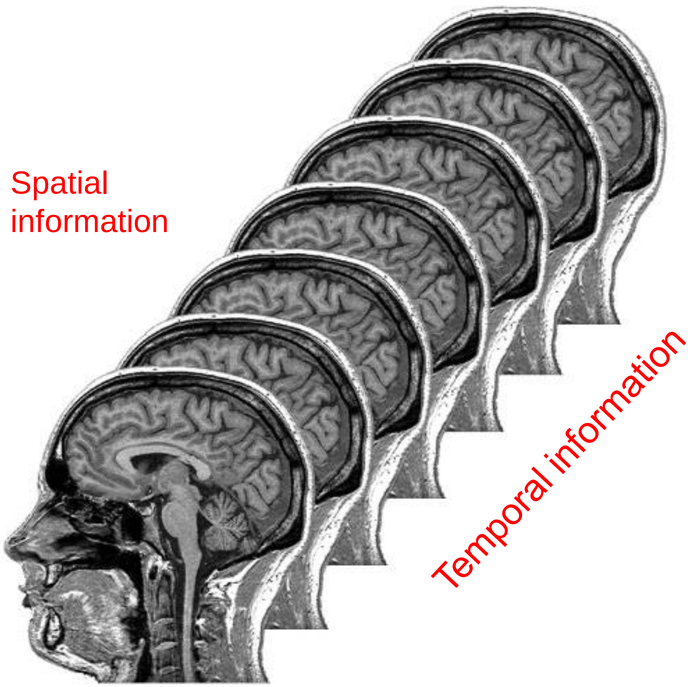


Multimodal data integration

Integrating fMRI and EEG – a challenge



Spatial information



Modelling simultaneously EEG and fMRI data is an open problem:
- different time scales
- different spatial resolution

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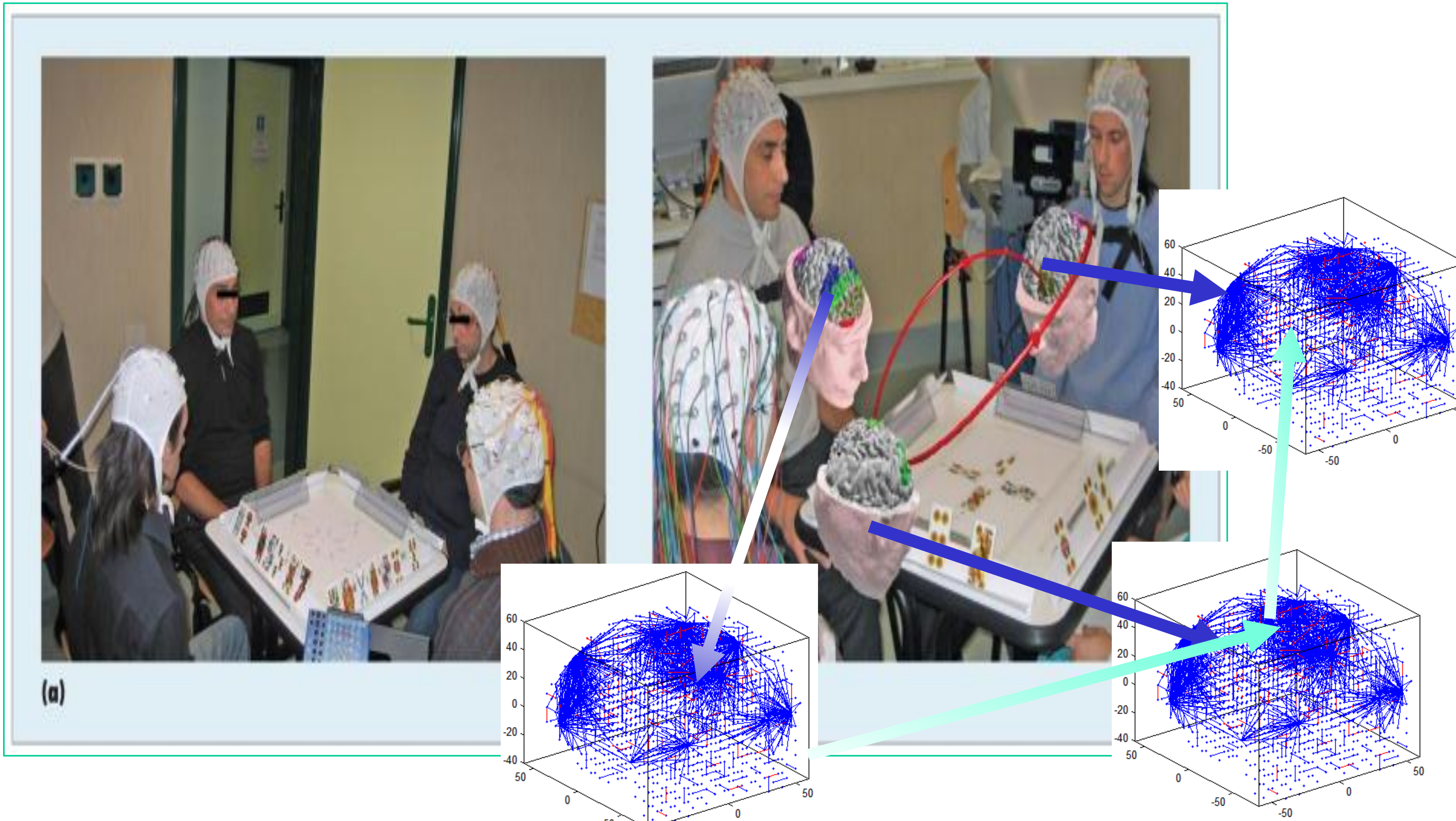
Understanding how humans synchronize and transfer knowledge between each other through hyper-scanning and using BI-SNN to model it



LAstolfi, J Toppi, FDe Vico Fallani, G Vecchiato, F Cincotti, C. Wilke, HYuan, D Mattia, S Salinari, B He, and F Babiloni, I, **Imaging the Social Brain by Simultaneous Hyperscanning During Subject Interaction,** EEE Intell Syst. 2011 Oct; 26 (5): 38–45.

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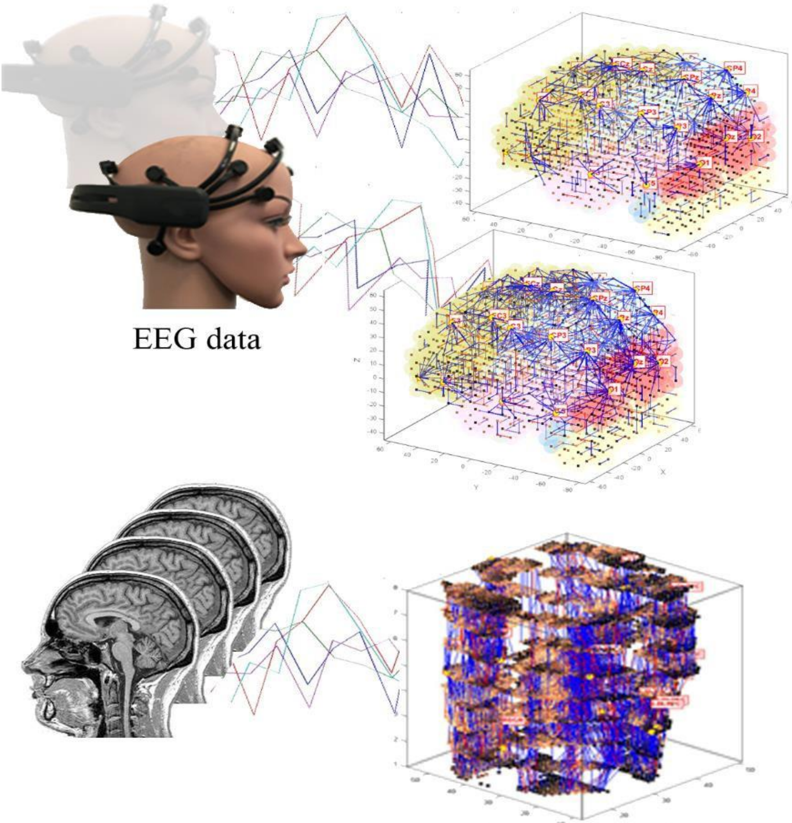
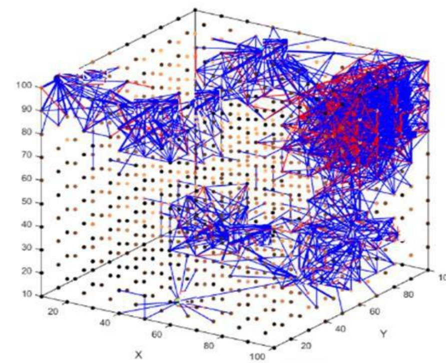
Knowledge-based human-machine symbiosis.
Conscious machines





Selected references

[1] Kasabov, N (2023). STAM-SNN: Spatio-Temporal Associative Memories in Brain-inspired Spiking Neural Networks: Concepts and Perspectives. TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.23723208.v1

[2] Kasabov, N.: NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Elsevier, Neural Networks, Vol. 52, pp. 62-76, doi:10.1016/j.neunet.2014.01.006 (2014).

[3] Kasabov, N., Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer-Nature (2019), https://www.springer.com/gp/book/9783662577134

[4] Kasabov, N., Tan, Y., Doborjeh, M., Tu, E., Yang, J., Goh, W., Lee, J. (2023): Transfer Learning of Fuzzy Spatio-Temporal Rules in the NeuCube Brain-Inspired Spiking Neural Network: A Case Study on EEG Spatio-temporal Data. IEEE Transactions on Fuzzy Systems, vol.31, issue 12, Dec.2023, 4542-4552, Print ISSN: 1063-6706, Online ISSN: 1941-0034, DOI: https://doi.org/10.1109/TFUZZ.2023.3292802,

[5] N. Kasabov, H.Bahrami, M.Doborjeh, A.Wang, Brain Inspired Spatio-Temporal Associative Memories for Neuroimaging Data: EEG and fMRI, Bioengineering 2023, MDPI 10(12), 1341 https://doi.org/10.3390/bioengineering10121341, www.mdpi.com/journal/bioengineering

[6] AbouHassan, I., Kasabov, N., Bankar, T., et al.: PAMeT-SNN: Predictive Associative Memory for Multiple Time Series based on Spiking Neural Networks with Case Studies in Economics and Finance. PrePrint, TechRxiv (2023).

[7] N K Kasabov. Life-long learning and evolving associative memories in brain-inspired spiking neural networks. MOJ App Bio Biomech. 2024;8(1):56–57, https://doi.org/10.15406/mojabb.2024.08.00208.

[8] N K Kasabov (2024). STAM-SNN: Spatio-Temporal Associative Memory in Brain-Inspired Spiking Neural Networks: Concepts and Perspectives. In: Kovács, L., Haidegger, T., Szakál, A. (eds) Recent Advances in Intelligent Engineering. Topics in Intelligent Engineering and Informatics, vol 18. Springer, https://doi.org/10.1007/978-3-031-58257-8_1

Thank you!

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