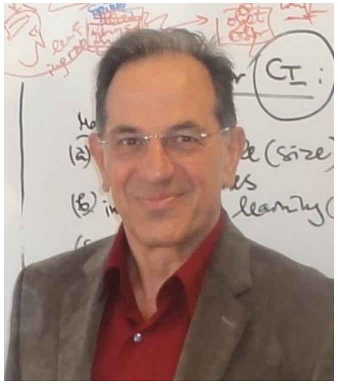
ISRC, Ulster University, October 2022

Brain-Inspired Spiking Neural Network Systems for Explainable and Life-Long Learning



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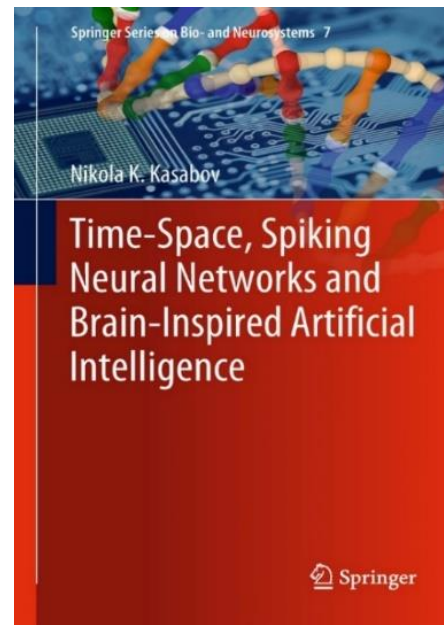
Abstract

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 not only capable of deep, incremental and life-long learning of temporal or spatio-temporal data, but also enabling the extraction of deep knowledge representation from the learned data.

1. Why brain-inspired computation?
2. BI-SNN architectures. NeuCube.
3. Application specific methods and systems
4. 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:

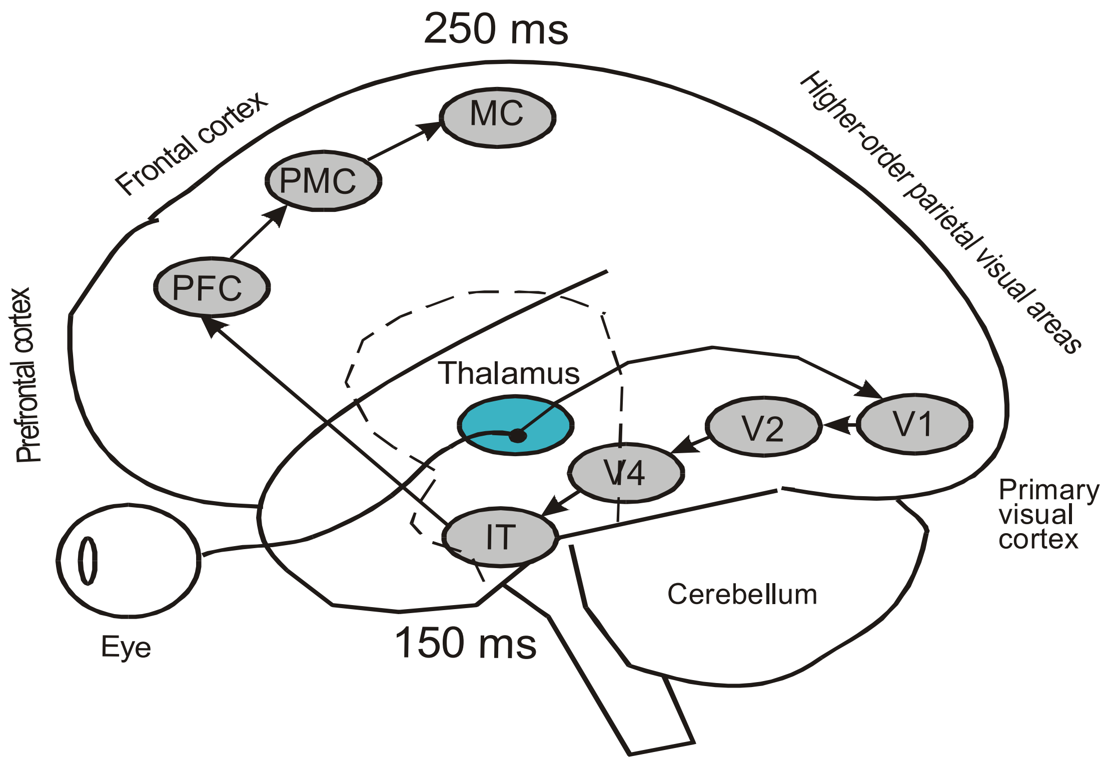
- short term (membrane potential);
- long term (synaptic weights);
- genetic (genes in the nuclei).

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.

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, 2007)

How is knowledge represented in the brain?

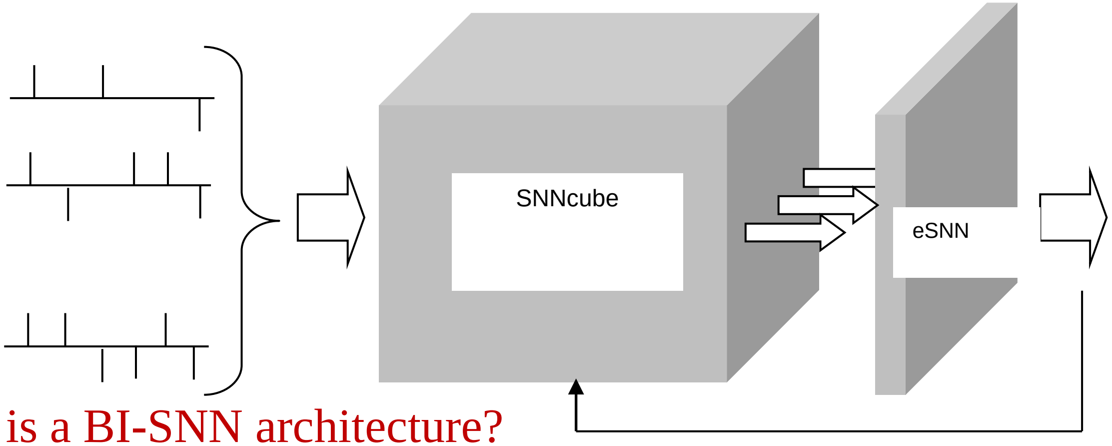
(1) Knowledge is spatio-temporal, in time and in space
(2) Represents informative patterns of multimodal data.
(3) Adaptable in an incremental, theoretically ‘life-long’ way.
(4) Self-organised, not restricted by fixed structures.
(5) Obtained in supervised-, unsupervised or semi-supervised modes.
(6) Robust to neuronal faults

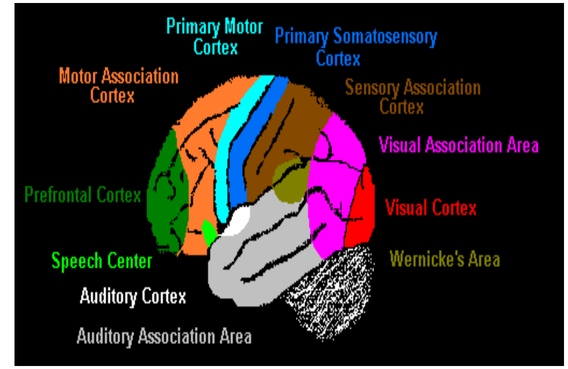
Deep knowledge is what the human brain learns and manifests all the time, exemplified by: Listening or/and playing musical pieces; Playing a game; Visual perception; Predicting the movement of a predator; All sorts of cognition; Decision making; Consciousness and *sub-consciousness*; ...and everything else the brain does.

The brain is universal machine for life-long learning and knowledge evolution.

The challenge:
Can we use these principles to build AI systems that can learn incrementally and possibly in a life-long learning mode and can be interpreted as knowledge discovery at any phase of their learning**.**

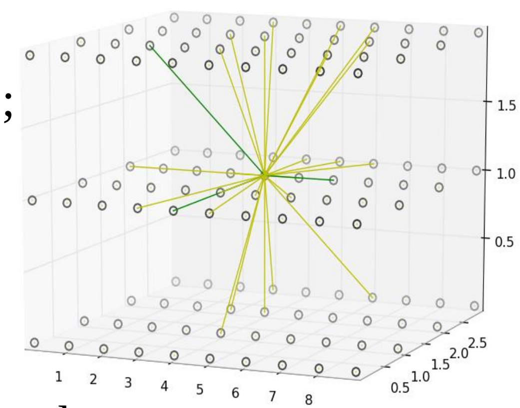
2. Brain-inspired SNN architectures (BI-SNN). NeuCube.





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, ….



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

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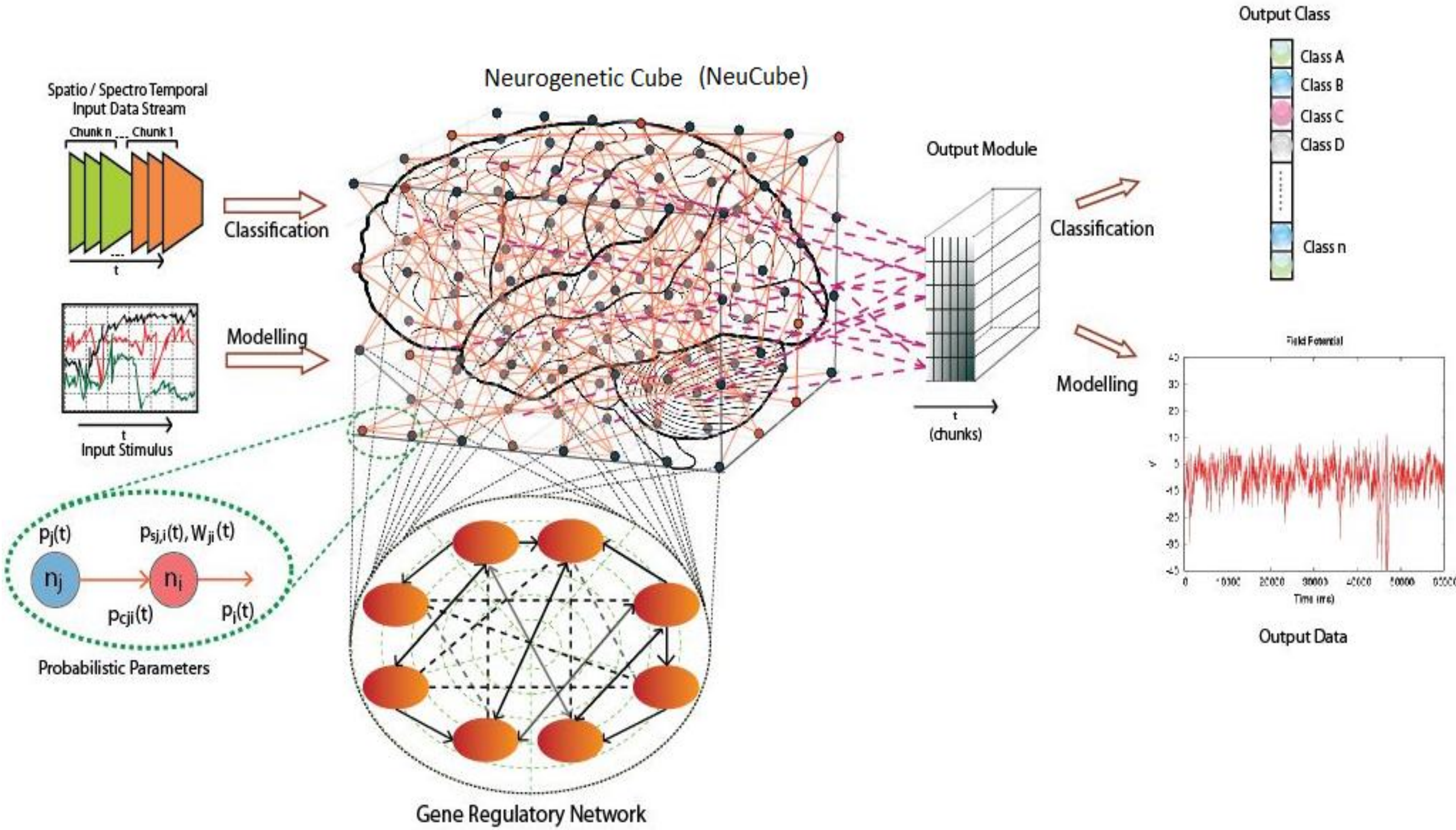
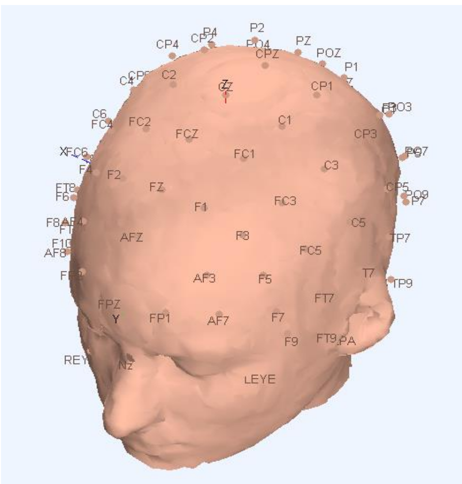
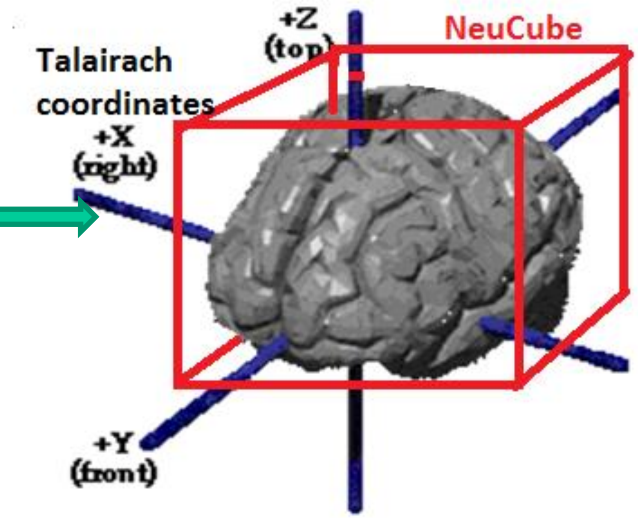
The NeuCube Architecture

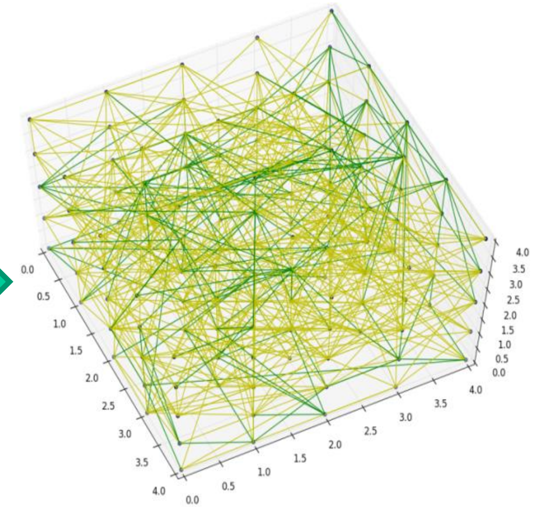


Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

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.

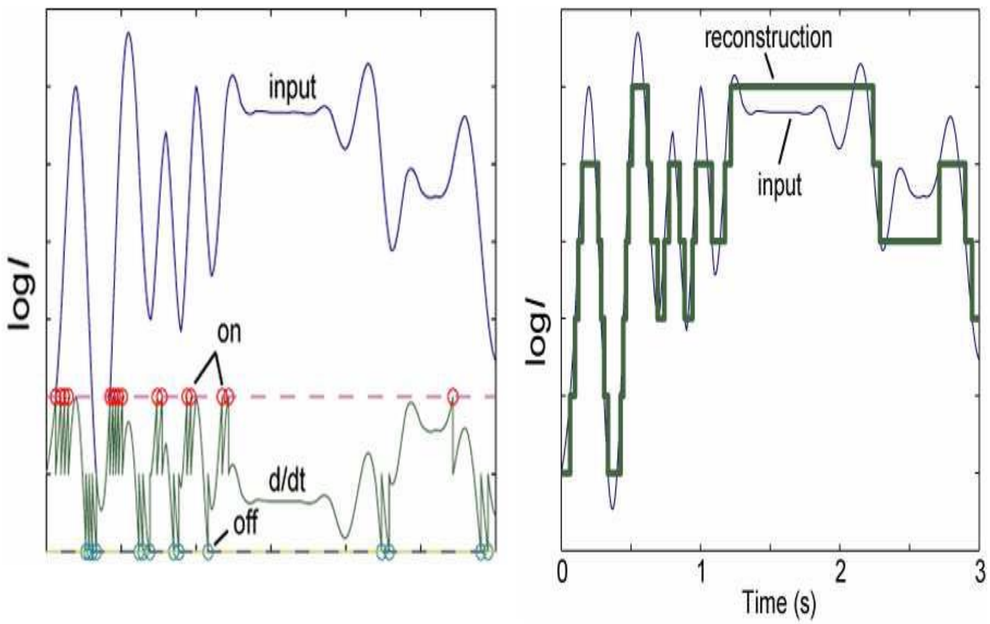
nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube

Spike encoding methods

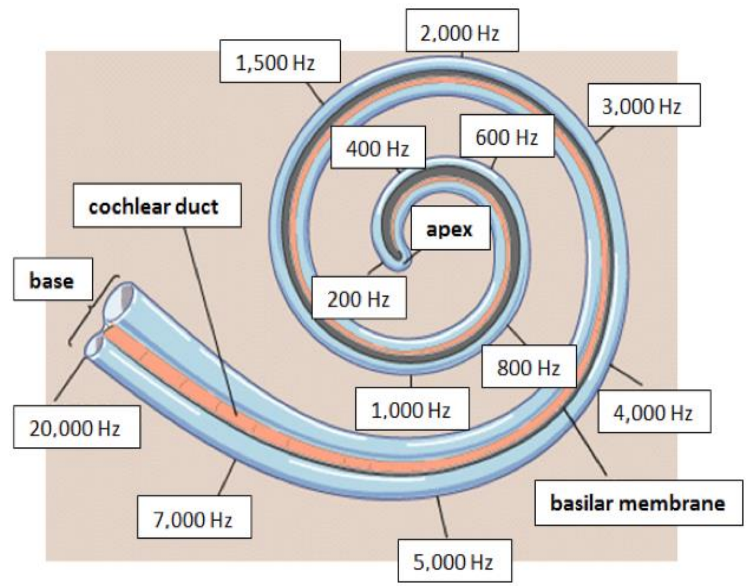
A spike is generated only if a change in the input data occurs beyond a threshold

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



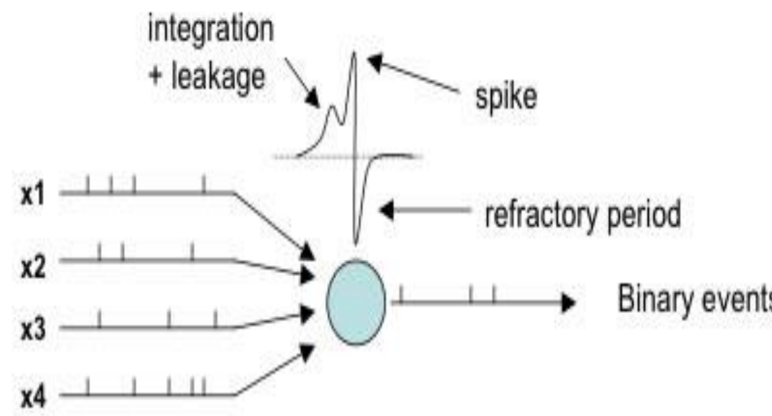
Tonotopic organization of the cochlea for spectro-temporal data

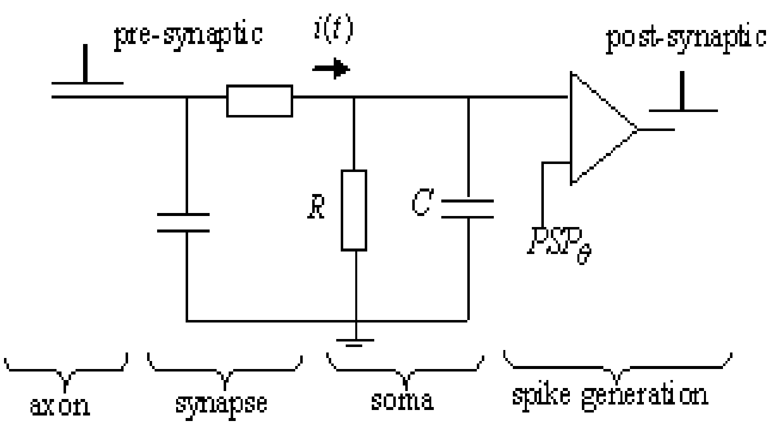
https://sites.google.com/site/jayanthinyswebite

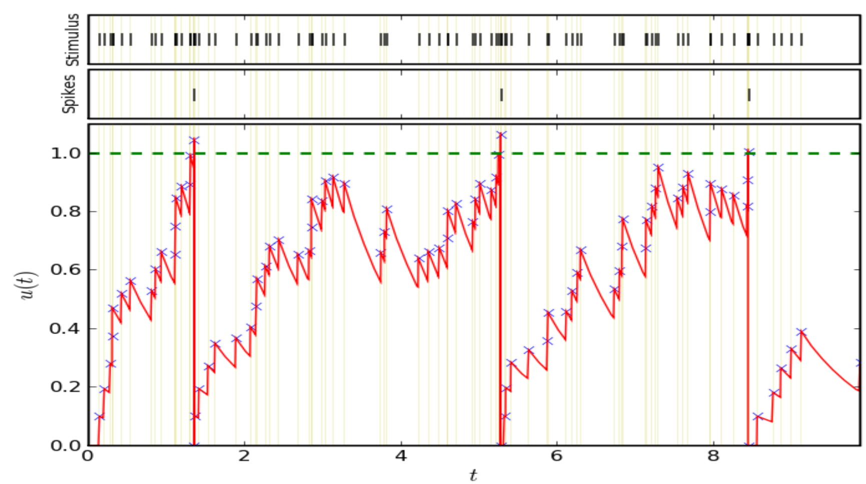
Spiking neuron models for BI-SNN

Models of a spiking neurons and SNN

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



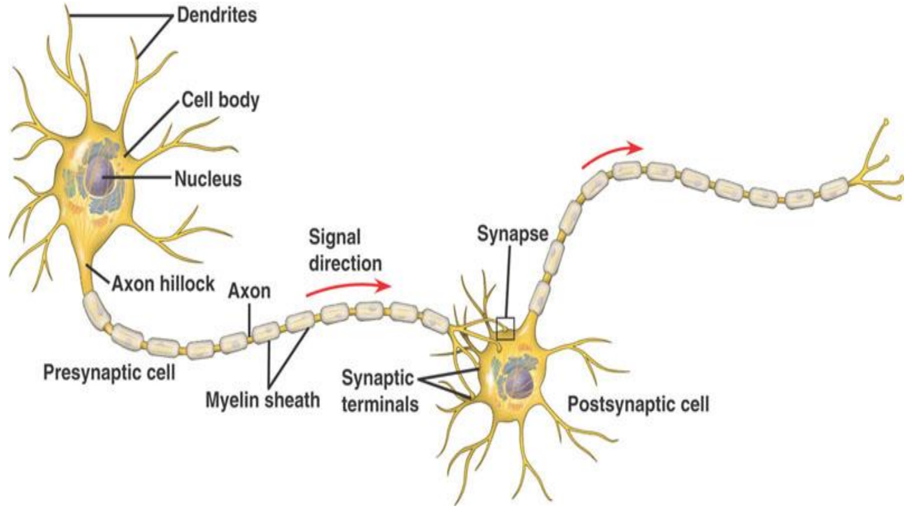




Methods for unsupervised learning in SNN

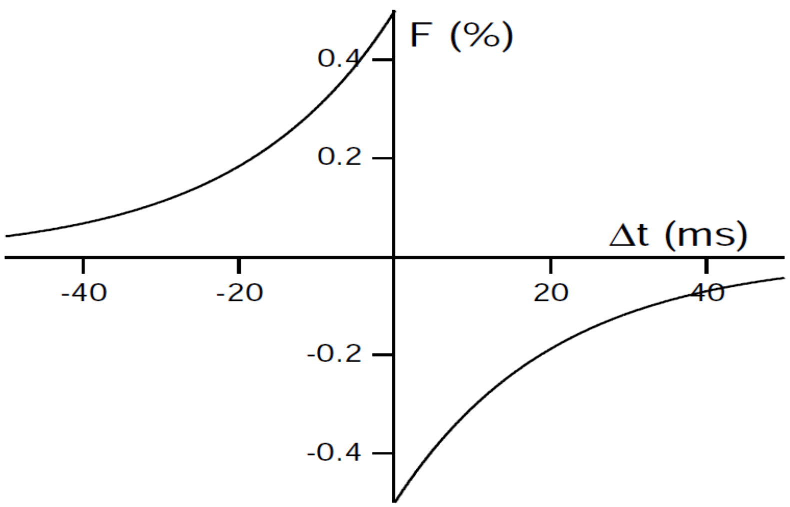
Spike-Time Dependent Plasticity (STDP)
(Abbott and Nelson, 2000).

- 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



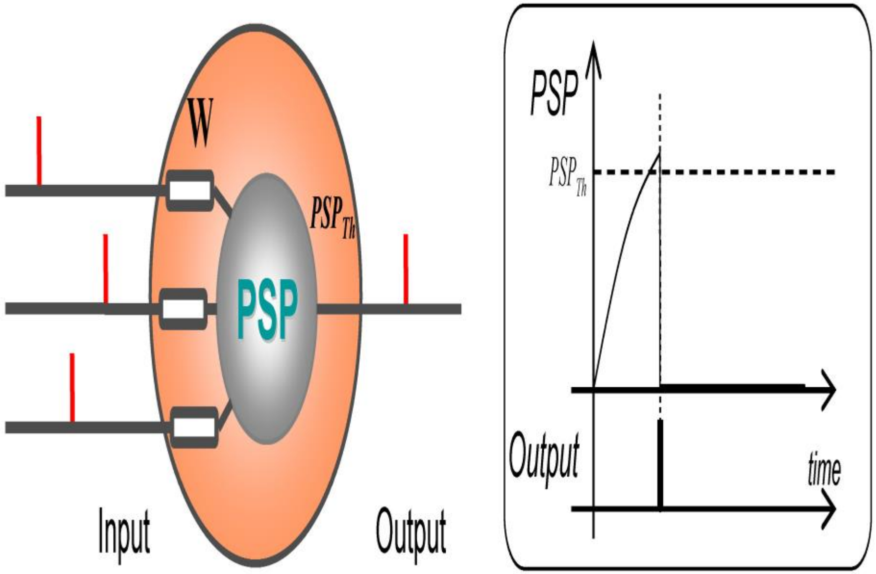
Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD:

$\Delta t = tpre - tpost$



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 $^{\text{order (j(t)}}$) $w_{j,i}$(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:

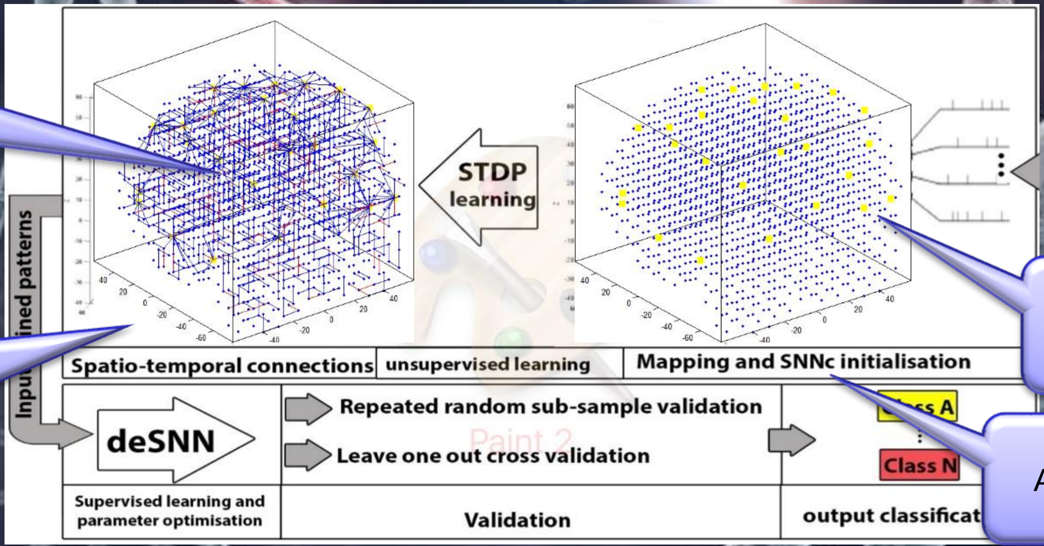
$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

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

wj,i(t) = ej(t) ▪ 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 learning in NeuCube



Creation of Neuron Connections During The Learning

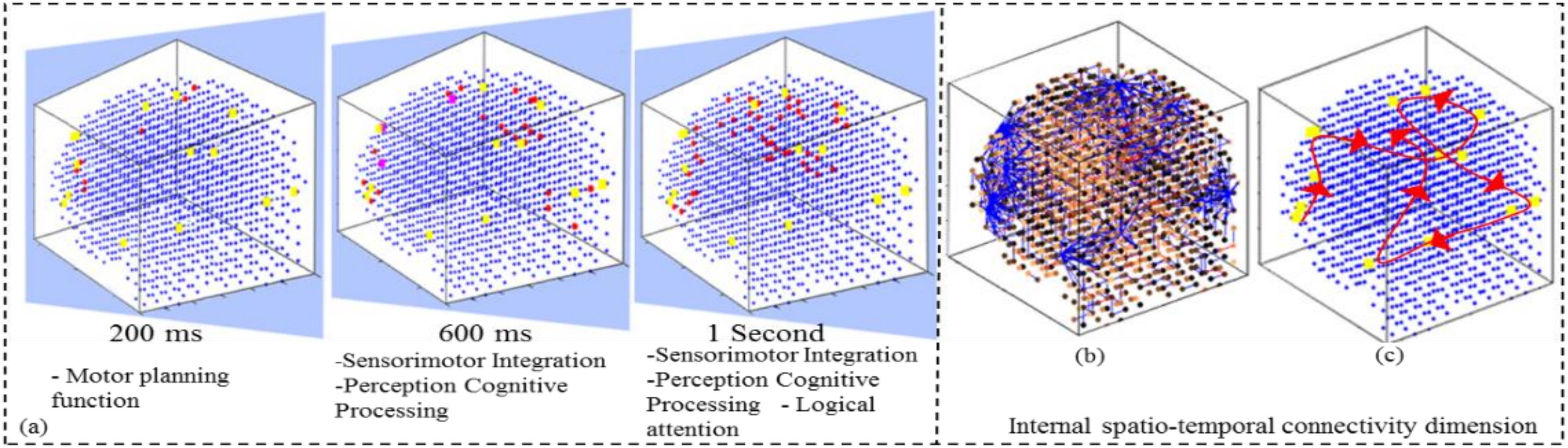
The More Spike Transmission, The More Connections Created

Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning

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,

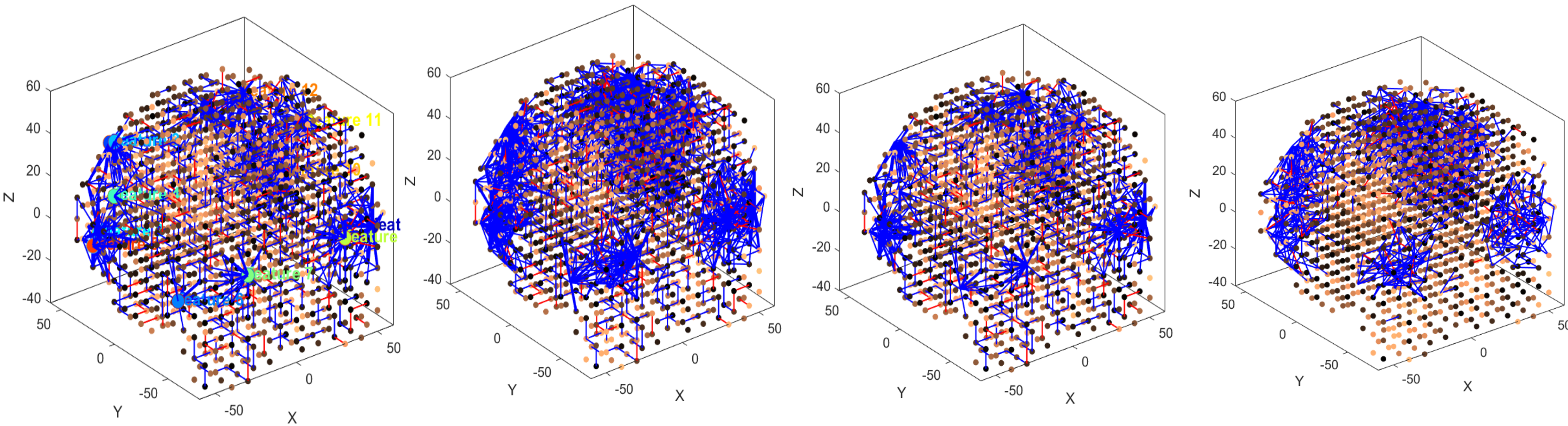
AND E2: Sensorimotor integration, in the Sensorimotor integration brain area, at time T2

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/

Life-long Learning (LLL) in the brain and in NeuCube

- ## How is LLL performed in the brain?

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

Neurogenesis
Neuromodulation
Episodic replay
Metaplasticity
Multisensory integration

- ## How LLL can be achieved in ANN?

G.I. Parisi, R.Kemker, J. L. Part, C. Kanan, S.Wermter, Continual lifelong learning with neural networks: A review, Neural Networks, 113, 2019, 54-71

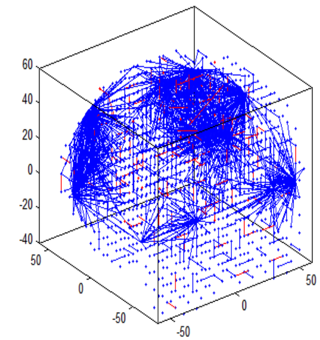
- ## How can LLL be achieved in NeuCube?

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

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

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

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).

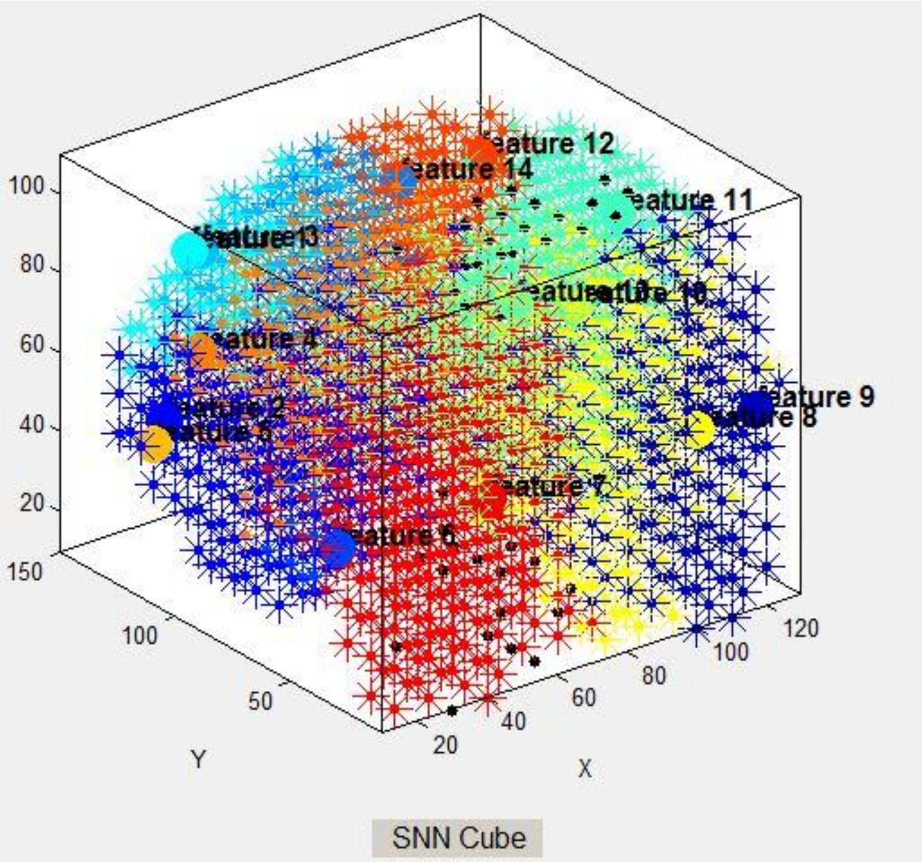
Such TSR representation can be as deep as needed (e.g. from tens to millions of linked events in time-space) depending on the *granularity* of discretization.

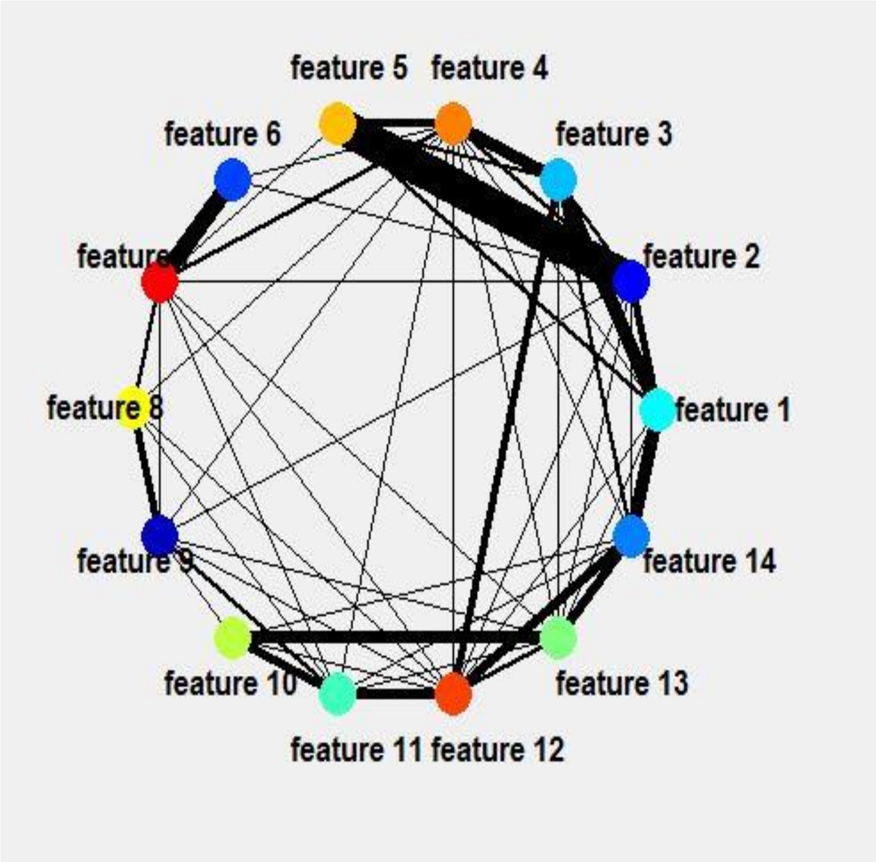
Capturing time-space knowledge as information exchange between clusters

- Clusters of highly connected neurons to input neurons;

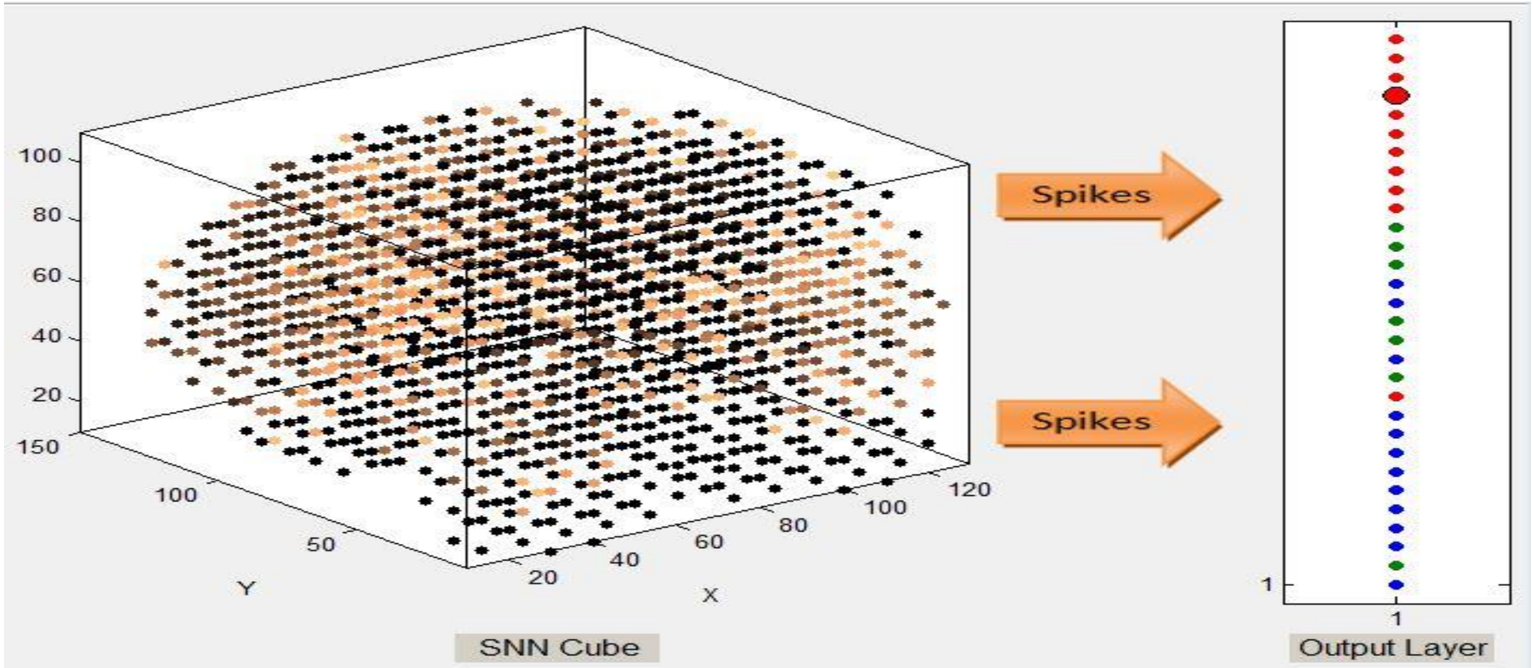
- Clusters of spiking activity spread from input neurons ;

- 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

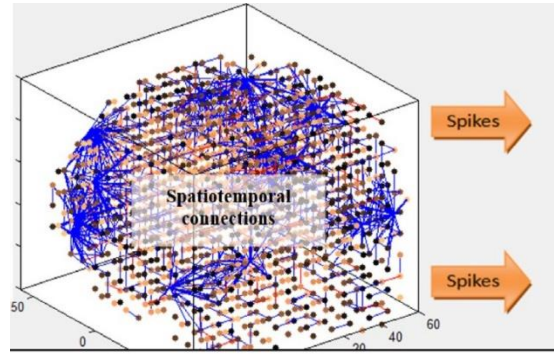
(area (Xk,Yk,Zk) with a cluster radius Rk is activated at time about T3) AND

(no other areas of the SNNcube are activated)

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

Extracting Time-Space Rules (TSR) 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.

NeuCube development environment for SNN system design for TSD

Implementation of SNN models: From von Neumann principles and Atanassov's ABC Machine to Neuromorphic Hardware

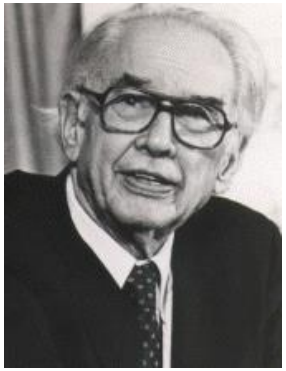
- The computer architecture of John von Neumann separates data and programmes (kept in the memory unit) from the computation (ALU); uses *bits*. First machine ABC by Atanassov and Berry.

- 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).

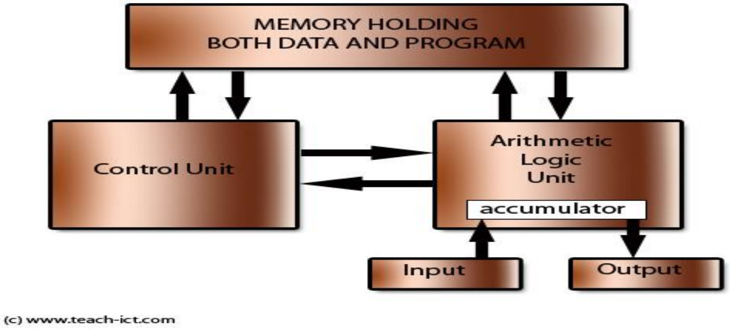
- A quantum computer uses *q-bits* (bits in a superposition) .

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).



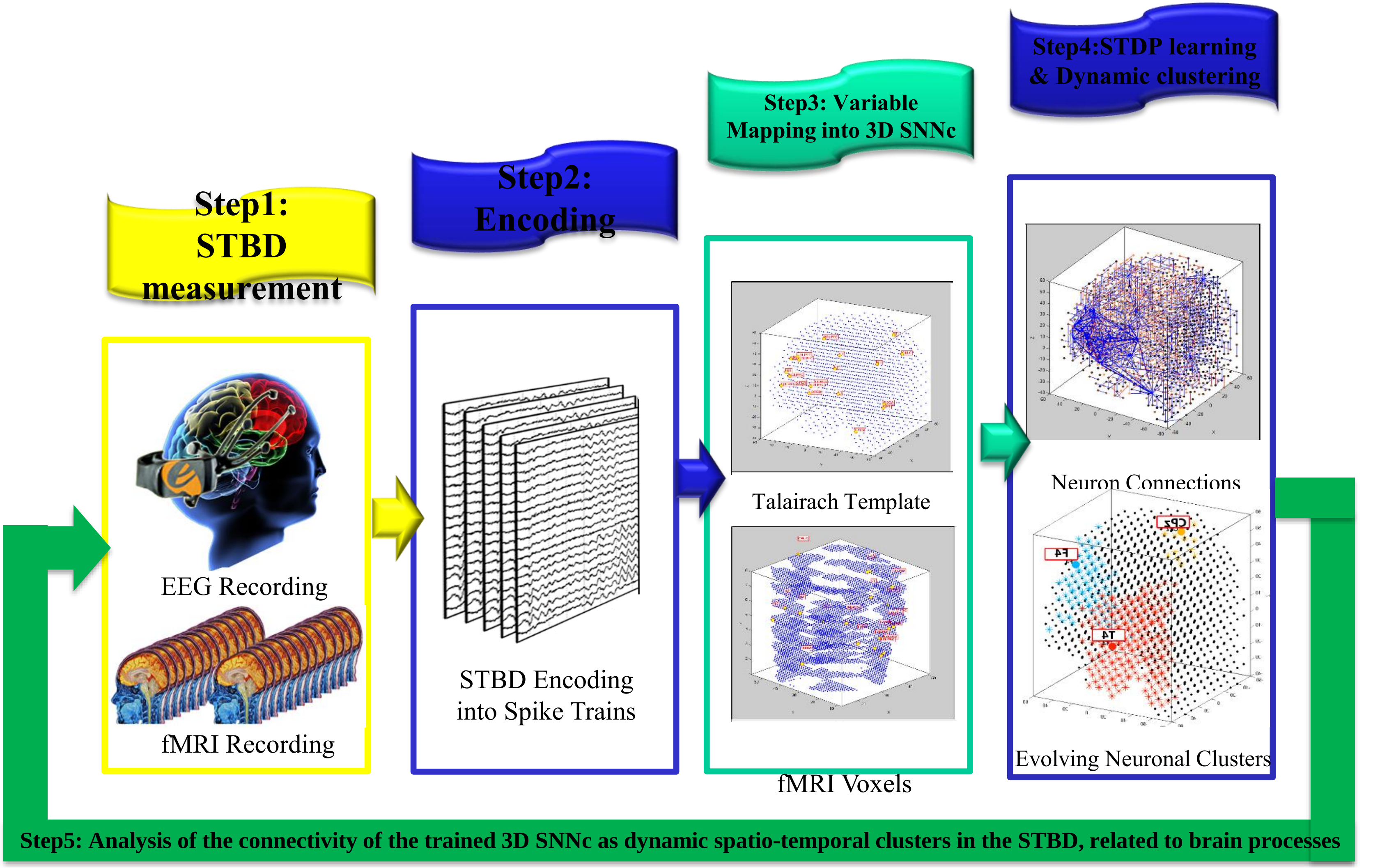
The Von Neumann or Stored Program architecture



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.

3. **Application specific methods and systems**

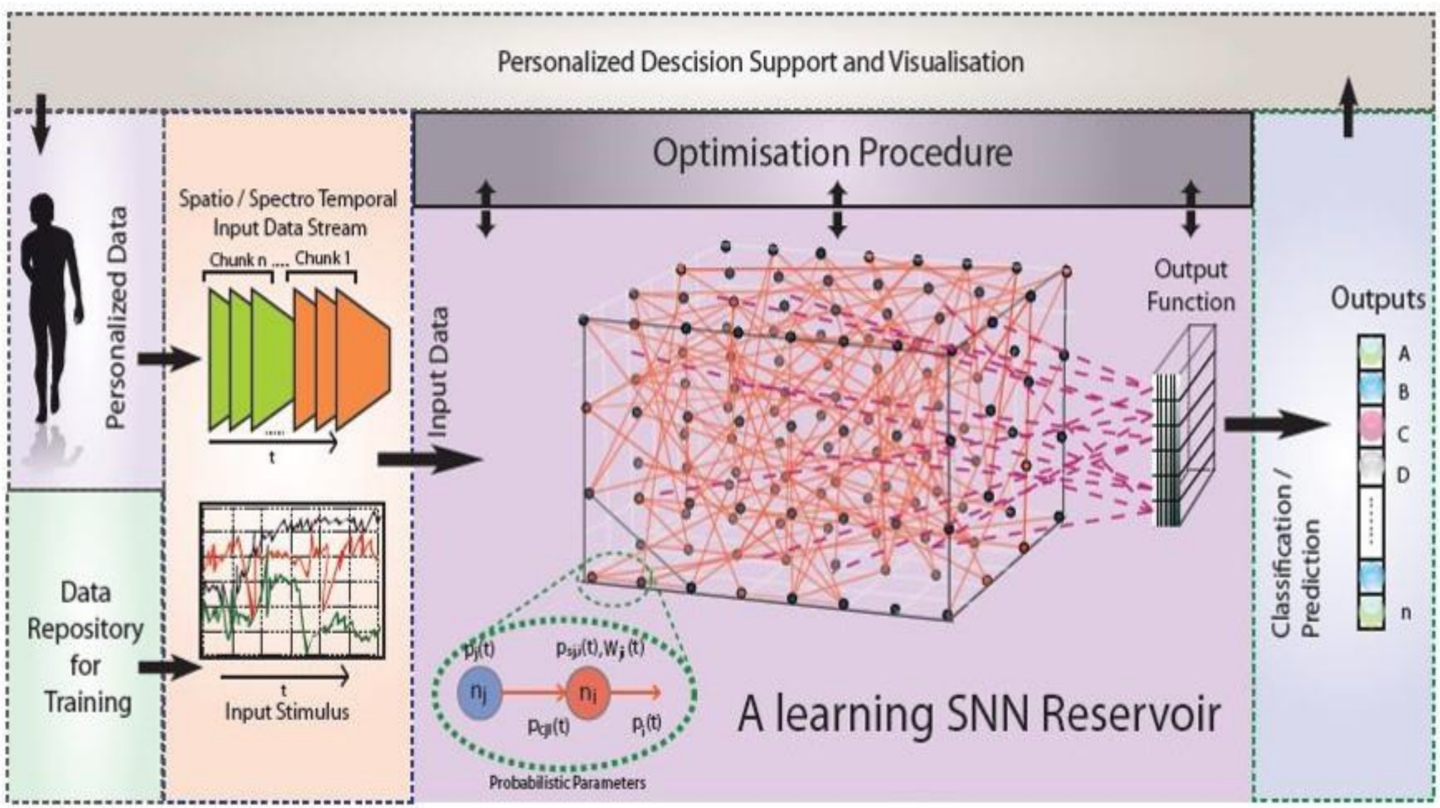
Deep learning and deep knowledge representation of neuroimaging spatio-temporal brain data



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

Personalised modelling for integrated static and dynamic data using NeuCube

N.Kasabov, V.Feigin, Z.Hou, Y.Chen, Improved method and system for predicting outcomes based on spatio/spectro-temporal data, PCT patent WO2015/030606 A2, US2016/0210552 A1, Publication date: 21 July 2016.

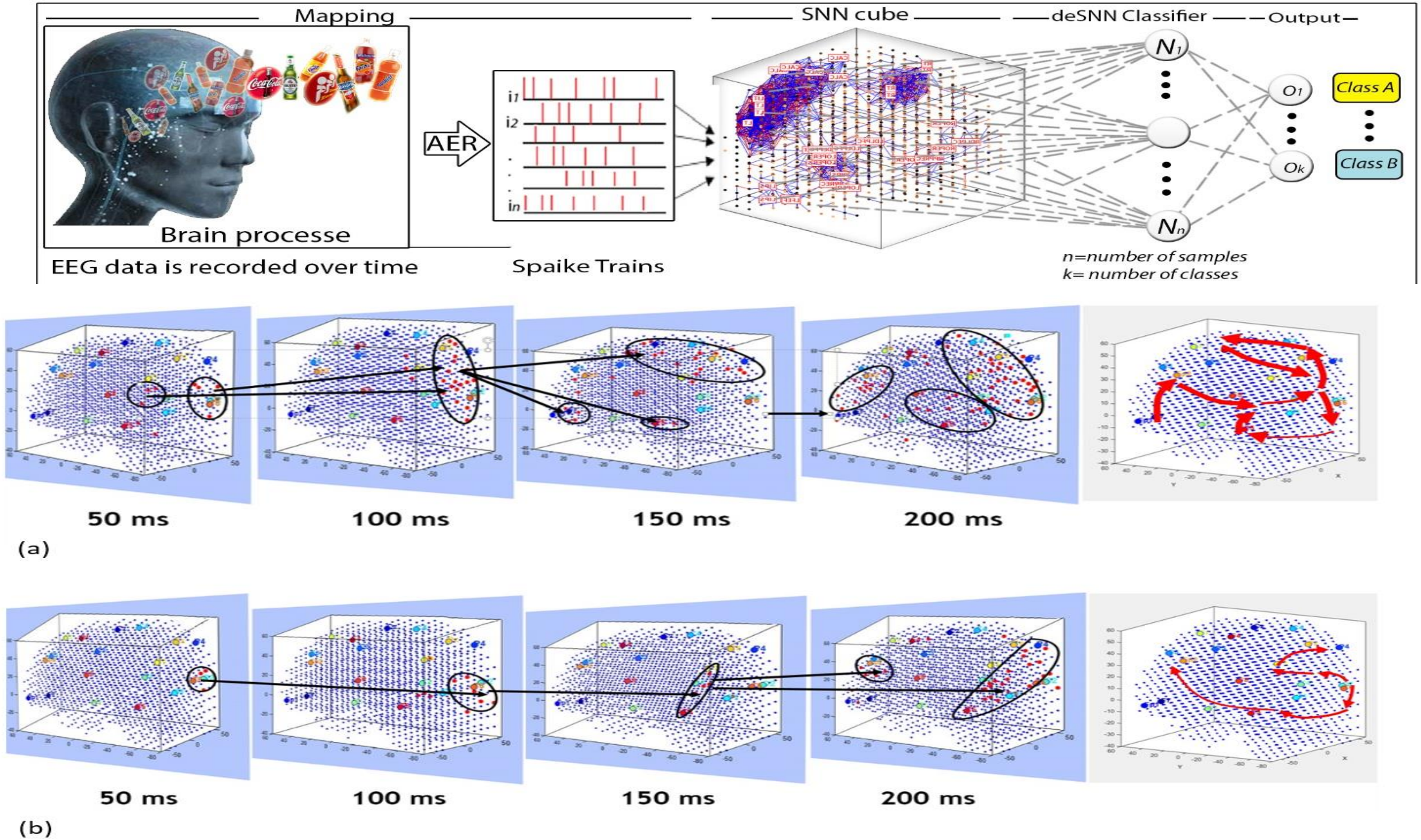


Current applications of PM in Neuroinformatics

Application	PM	Other AI methods accuracy	n
Schizophrenia Predicting formal diagnosis in next six months using gene expression measures from blood test	98%	92-97.5%	84
Mindfulness Treatment Predicting response to depression treatment using EEG data	73%	48.5-58.5%	20
Methadone Predicting treatment programme outcome using EEG data	91%	60-63%	67
Stroke Predicting stroke events using patient and environmental data	94%	67.5-87.5%	1200
AD/MCI/normal Prediction 2 years ahead	91%	40% (LSTM)	175

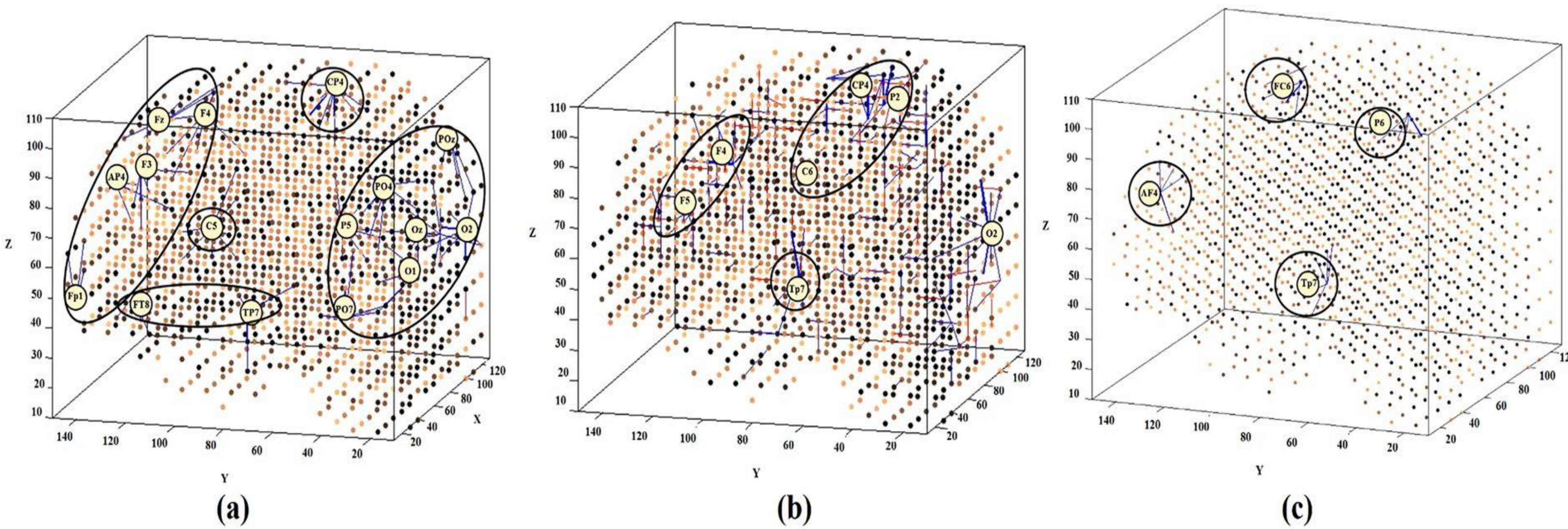
Understanding human decision making

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)

Understanding brain re-wiring due to mindfulness training using EEG

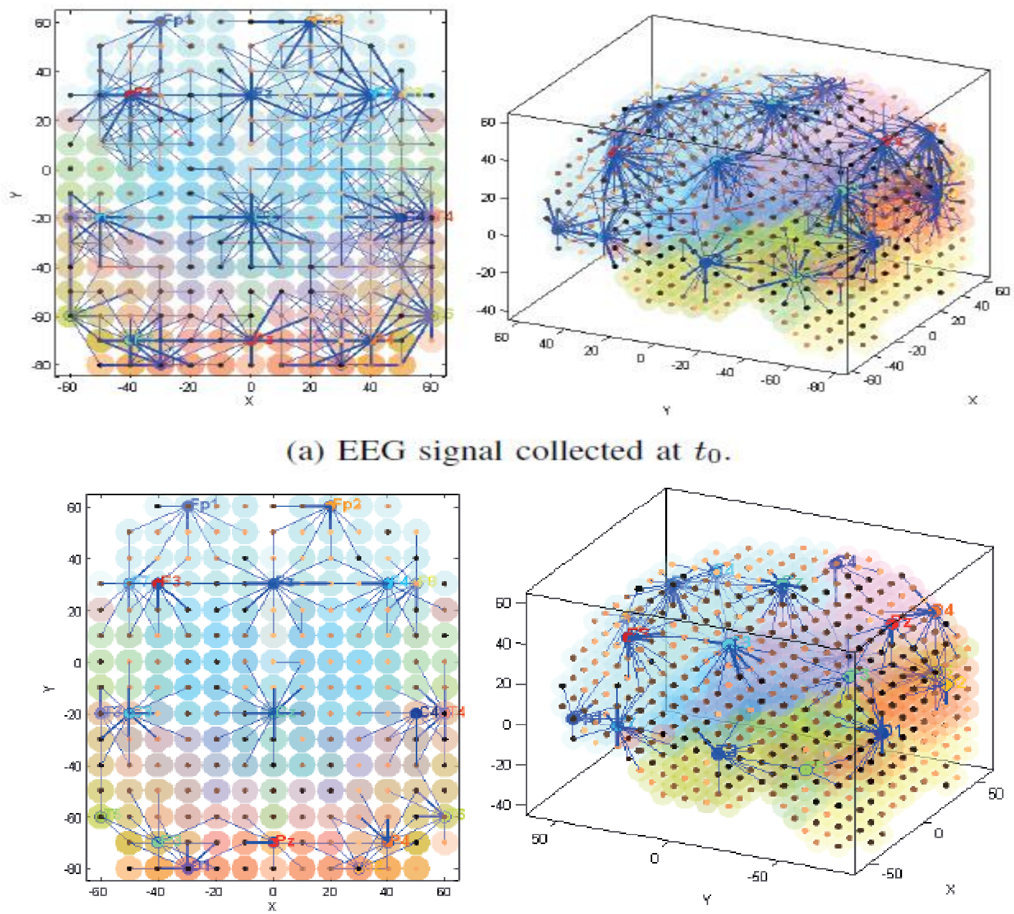


Differences between the connectivity in the trained SNN models of T1 (prior to MT) and T2 (post training) in (**a**) non-depressed (ND) group, (**b**) responsive-depressed (D+) group, and (**c**) unresponsive depressed (D−) group. The connections in each neural cluster represent the areas of main changes in the EEG after MT.

Z. Doborjeh, M. Doborjeh, T. Taylor, N. Kasabov, G. Y. Wang, R. Siegert, A. Sumich, Spiking Neural Network Modelling Approach Reveals How Mindfulness Training Rewires the Brain, **Nature,** Scientific Reports, (2019) 9: 6367, https://www.nature.com/articles/s41598-019-42863-x (top 100 papers for 2019)

Predicting progression of MCI to AD (in months)

E.Capecci, Z.Doborjeh, N.Mammone, F. La Foresta, F.C. Morabito and N. Kasabov, Longitudinal Study of Alzheimer's Disease Degeneration through EEG Data Analysis with a NeuCube Spiking Neural Network Model, Proc. WCCI - IJCNN 2016, Vancouver, 24-29.07.2016, IEEE Press.



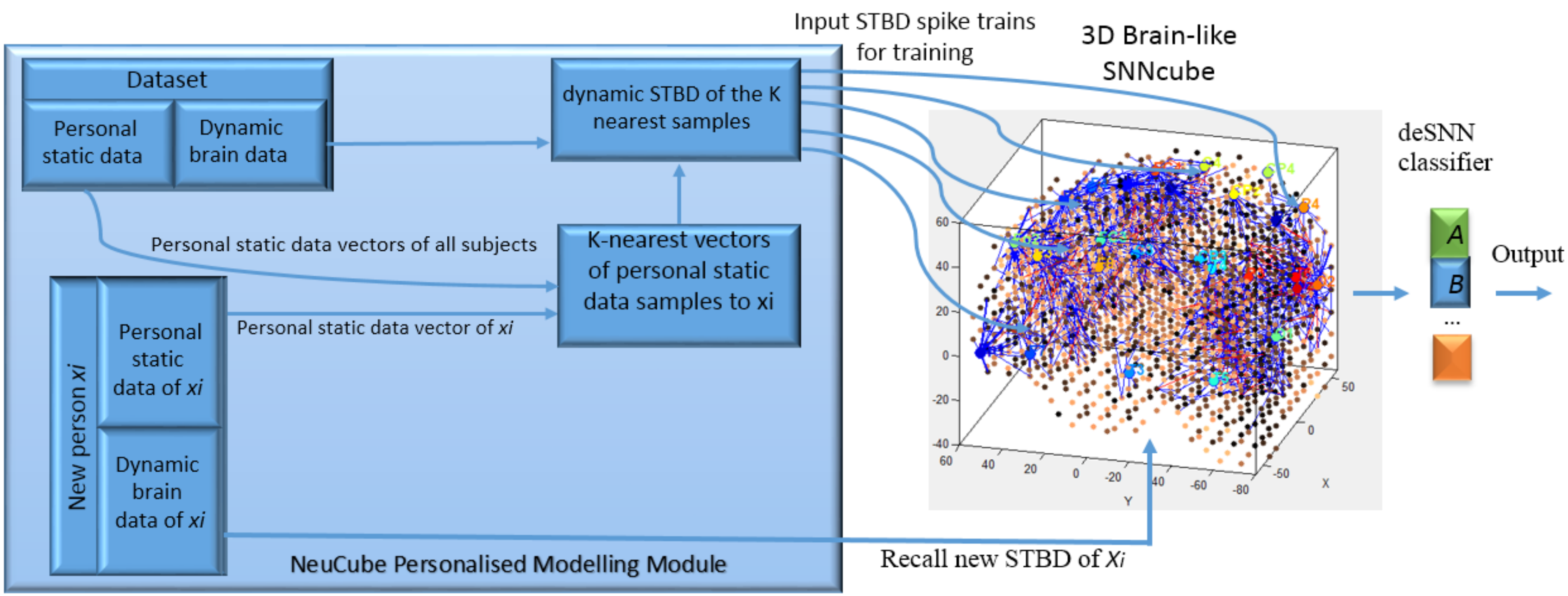
(a) EEG signal collected at t_0.

(b) EEG signal collected at t_1.

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.

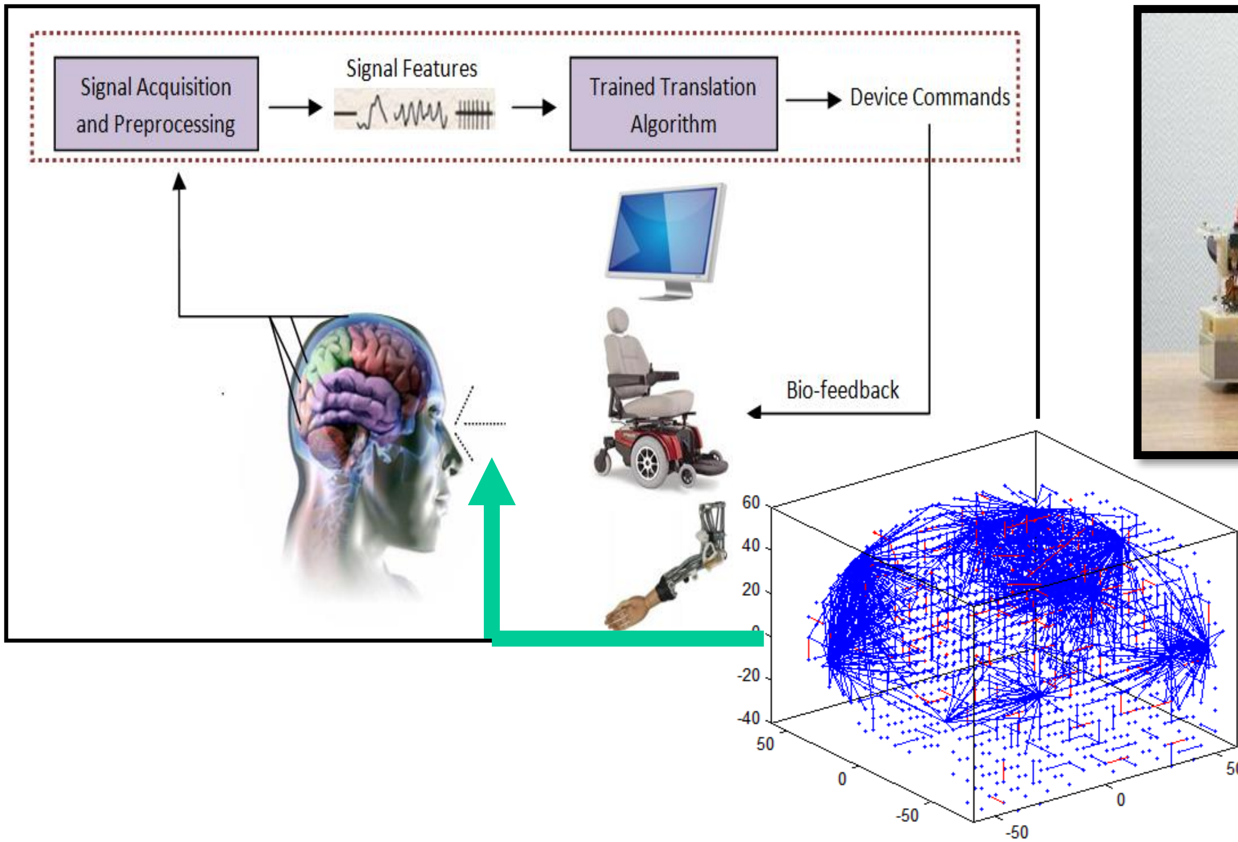


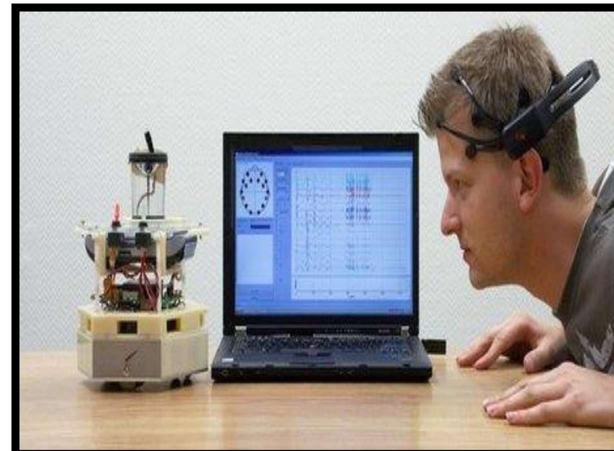
Methods	NeuCube-Personalised modelling	NeuCube- Global modelling
Classification accuracy of class M versus class OP in %	Averaged over 47 trained PSNN models: 93.61	One trained SNN model using all subjects and tested via leave-one-out method: 79.00

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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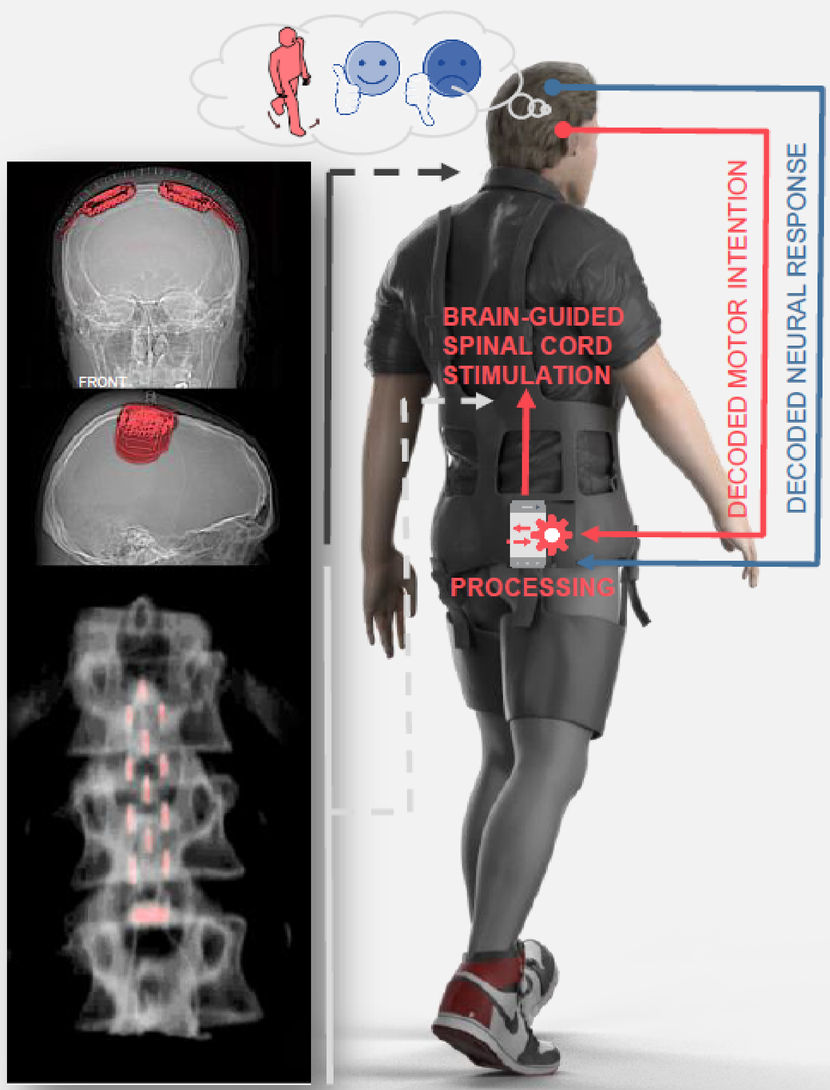
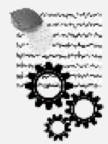
Fully embedded auto-adaptive Brain Machine Interface



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

- 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

IICT- BAS

Brain-guided spinal cord Stimulation

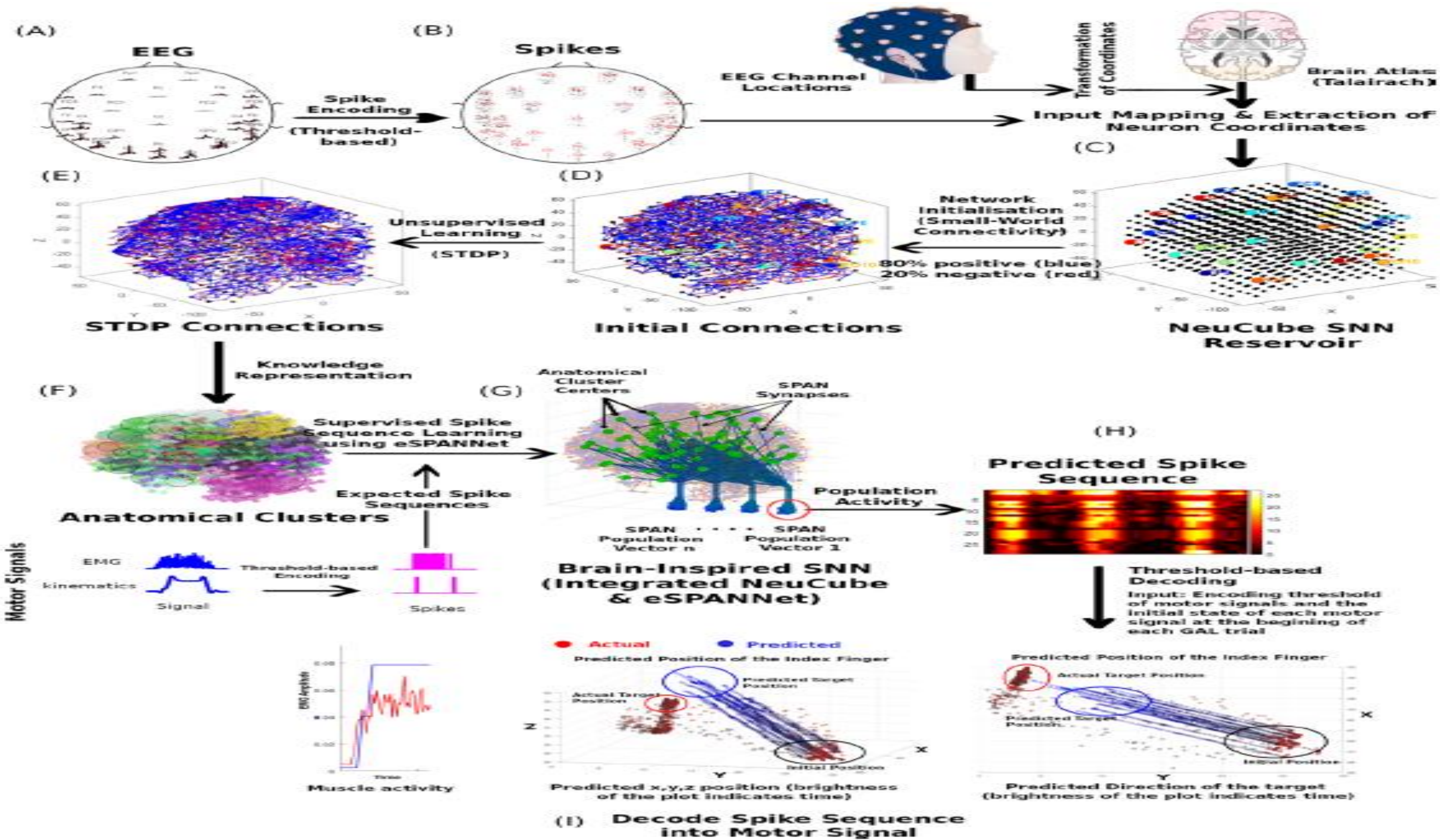
- Epidural Electrical Targeted dynamic stimulation
- Auto-adaptative stimulation Patterns

Miniaturization of BMI technology

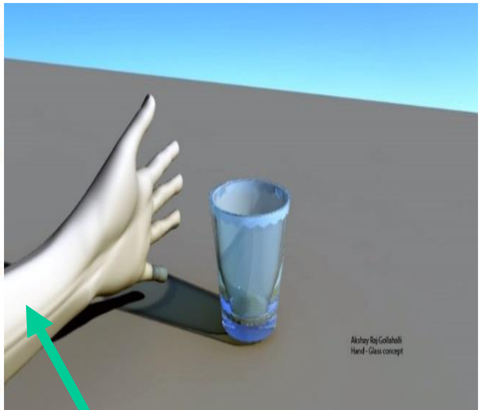
- Low power integrated circuit for accelerating the decoding algorithms
- High system level integration
- Portable battery-powered solution

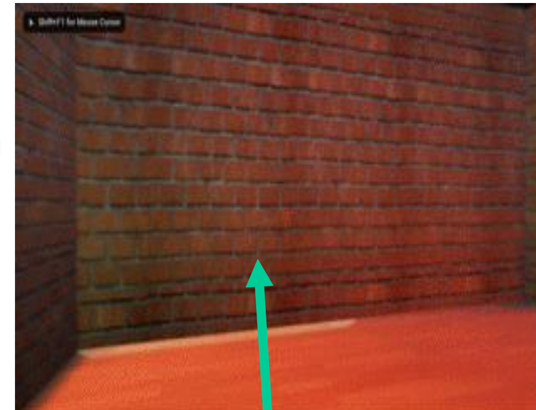
BI-SNN for neurorehabilitation

Kumarasinghe, K., Kasabov, N. & Taylor, D. Brain-inspired spiking neural networks for decoding and understanding muscle activity and kinematics from electroencephalography signals during hand movements. *Sci Rep* **11,** 2486 (2021). https://doi.org/10.1038/s41598-021-81805-4 (ranked 11 in Nature SR in Neuroscience for 2021)



Learning and understanding brain-VR/AR interaction in time-space

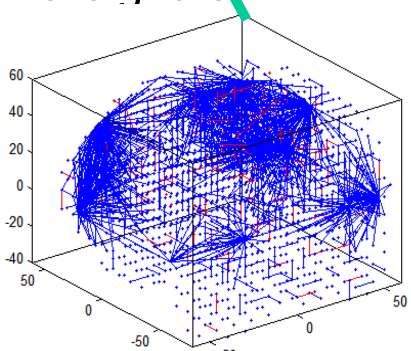


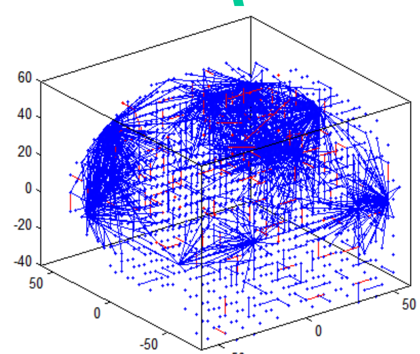


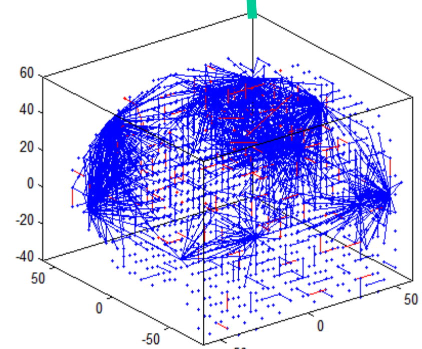
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.

A virtual environment to control a quadrotor using EEG signals.

A virtual environment (3D) using Oculus rift DK2 to move in an environment using EEG.



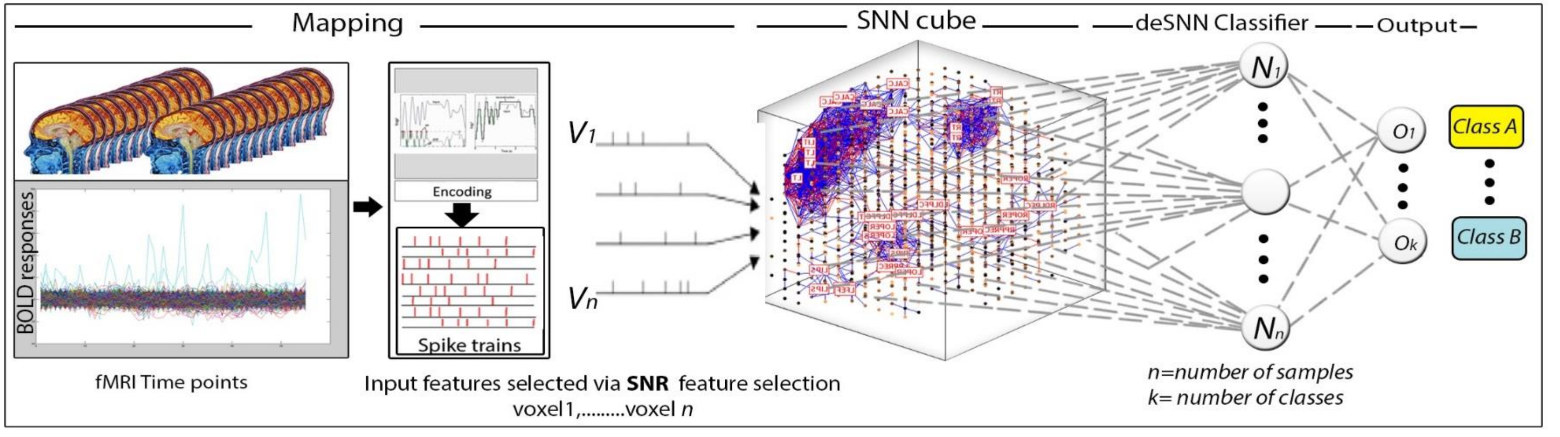




Deep learning and deep knowledge representation of fMRI data

(Spatial mapping of fMRI voxels into a 3D SNN cube after conversion into Talairach coordinates.

N.Kasabov, M.Doborjeh, Z.Doborjeh, IEEE Transactions of Neural Networks and Learning Systems, DOI: 10.1109/TNNLS.2016.2612890,2016

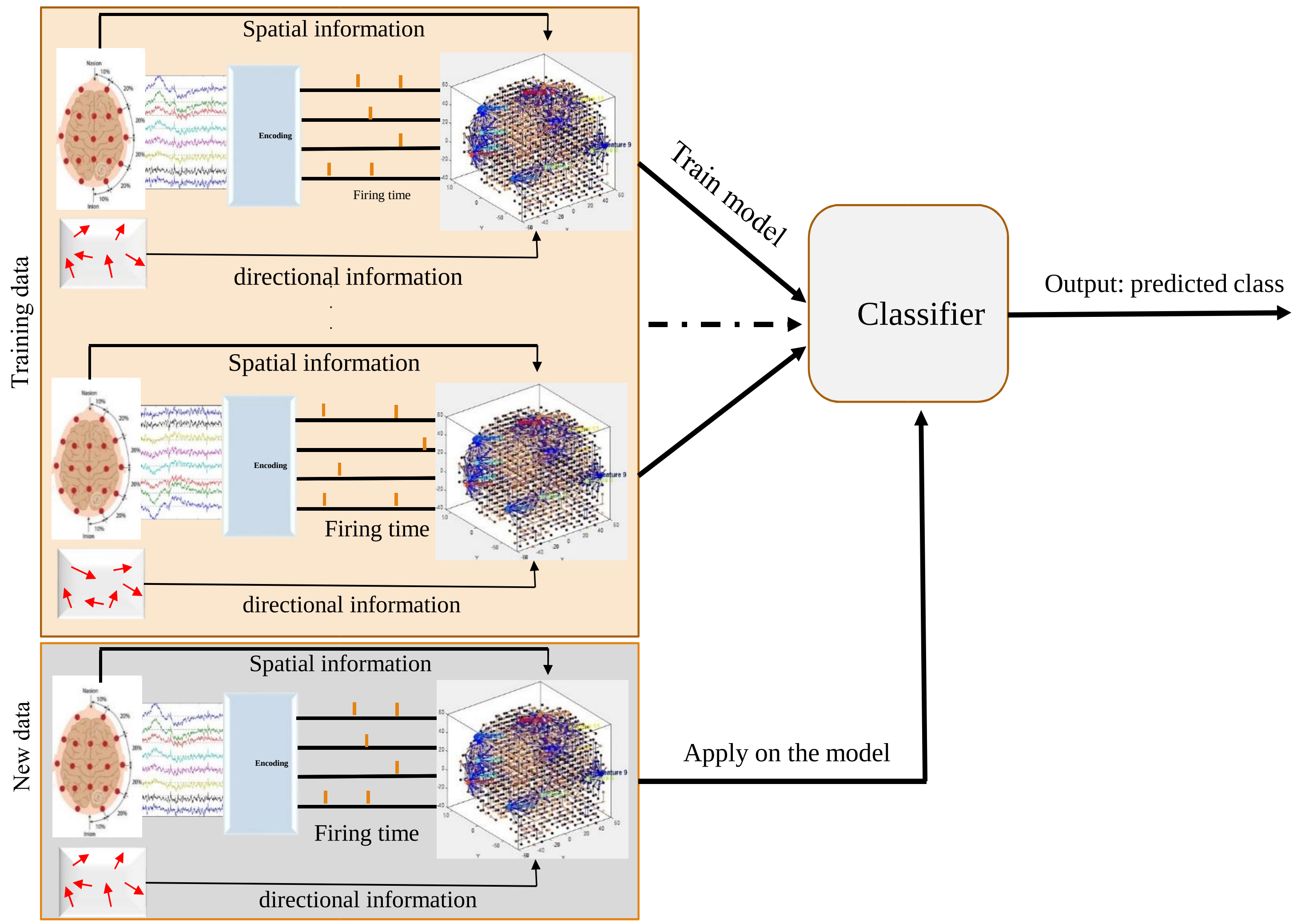


Method / Subject From STAR+ data (picture vs sentence perception)	SVM	MLP	NEUCUBE[B]
04799	50(20,80)	35(30,40)	90(100,80)
04820	40(30,50)	75(80,70)	90(80,100)
04847	45(60,30)	65(70,60)	90(100,80)
05675	60(40,80)	30(20,40)	80(100,60)
05680	40(70,10)	50(40,60)	90(80,100)
05710	55(60,50)	50(50,50)	90(100,80)

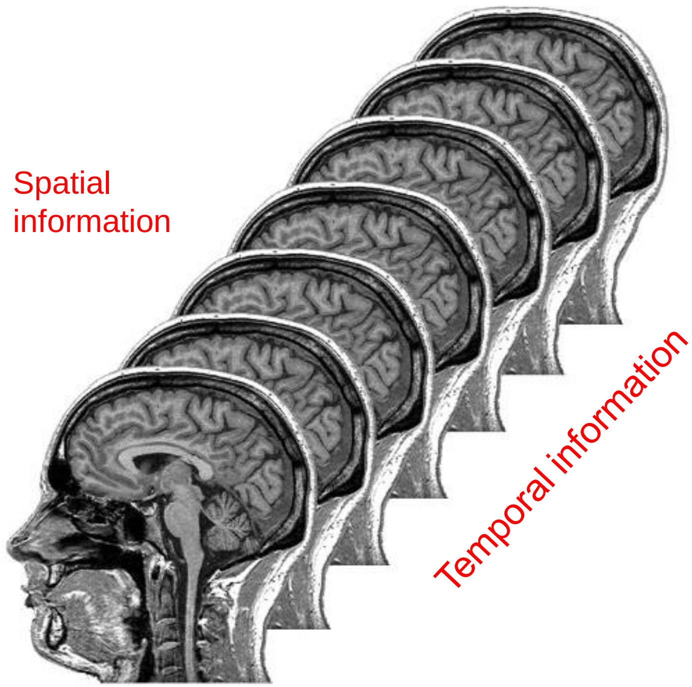
PM using both fMRI and DTI data

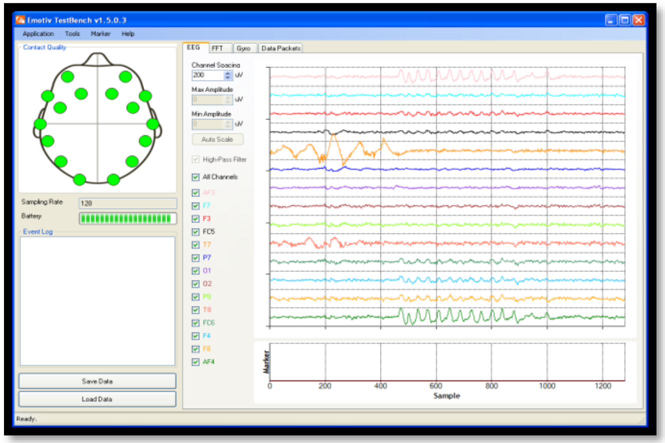
Case on response of schizophrenic patients to clozapine

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



Integrating fMRI and EEG – a challenge





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

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Using BI-SNN as universal machines for explainable and life-long learning systems for various spatio/spectro -temporal data

Examples:

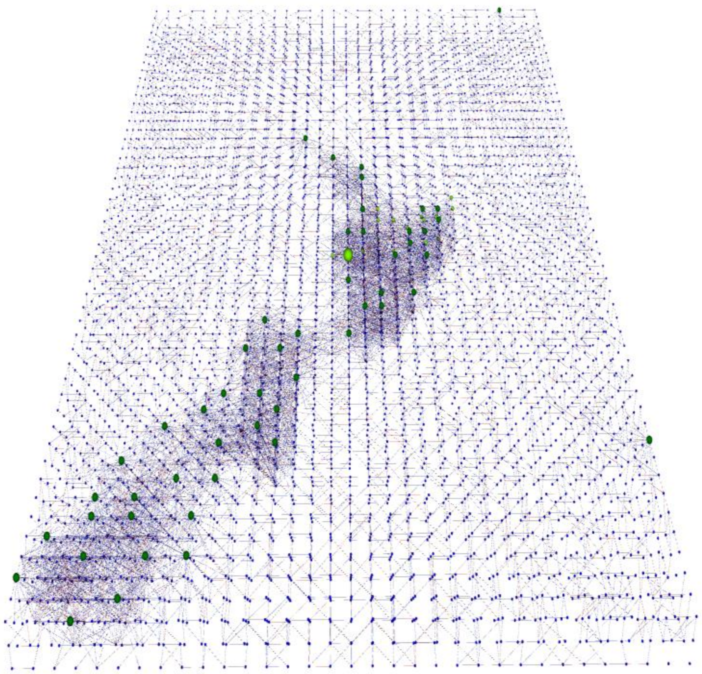
1) Environmental streaming data (e.g. predicting individual stroke)

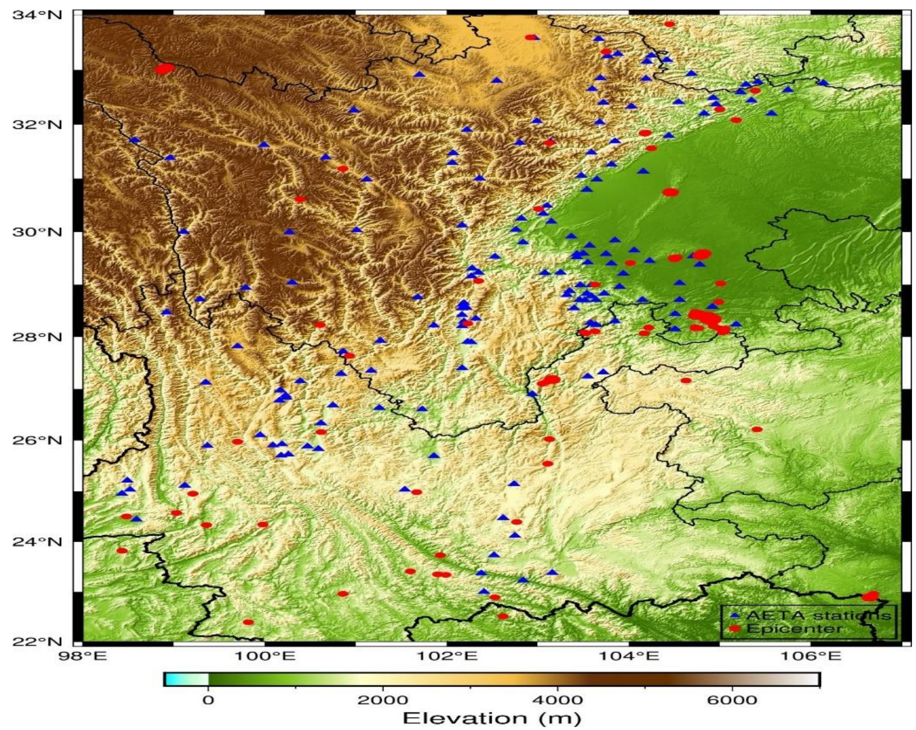
2) Moving object recognition

3) Multisensory systems for predicting pollution, floods, earthquakes

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

4) AETA system in China.

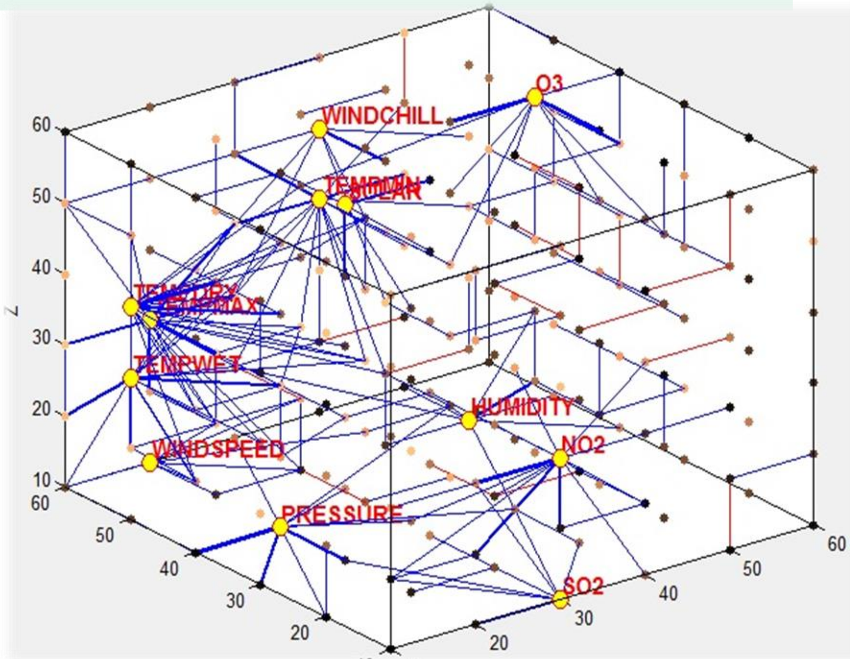


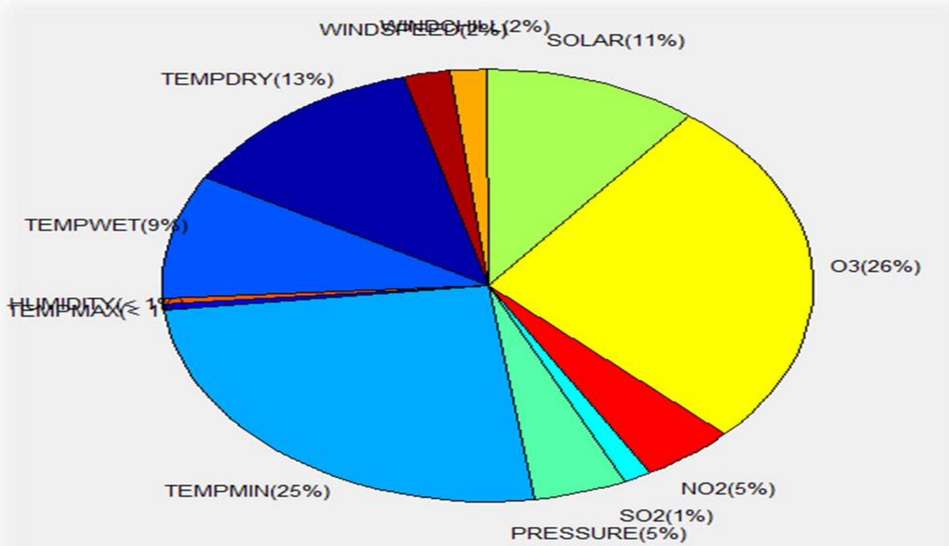


Personalised prediction of risk for stroke days ahead

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

METHODS	SVM	MLP	KNN	WKNN	NEUCUBEST
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

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).

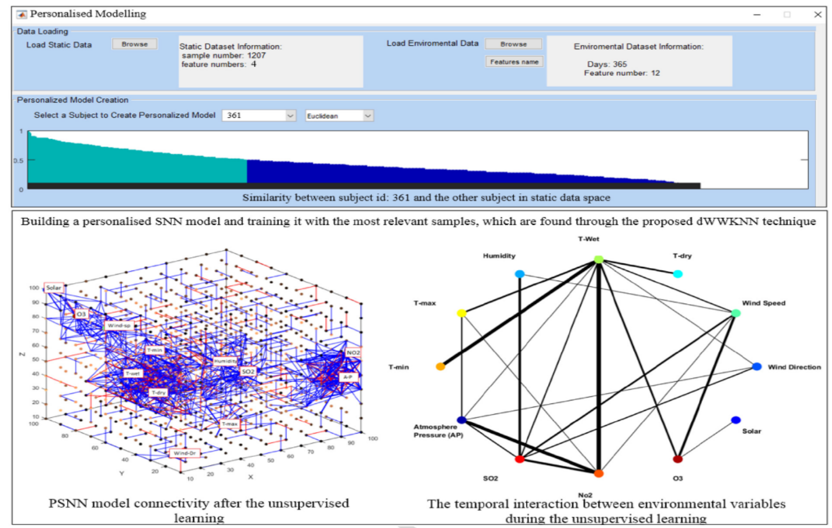


Fig. 9. The user interface of the proposed personalised predictive system for prediction of risk of stroke. A PSNN model is created to spatially map the environmental variables, where the most correlated variables are mapped to closer input neurons. Then the PSNN model was trained on the temporal spike 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.

4. Discussions and future directions

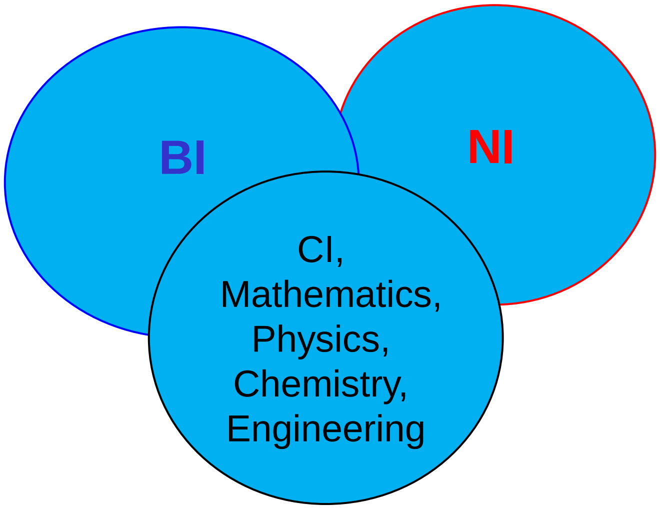
Advantages of BI-SNN:

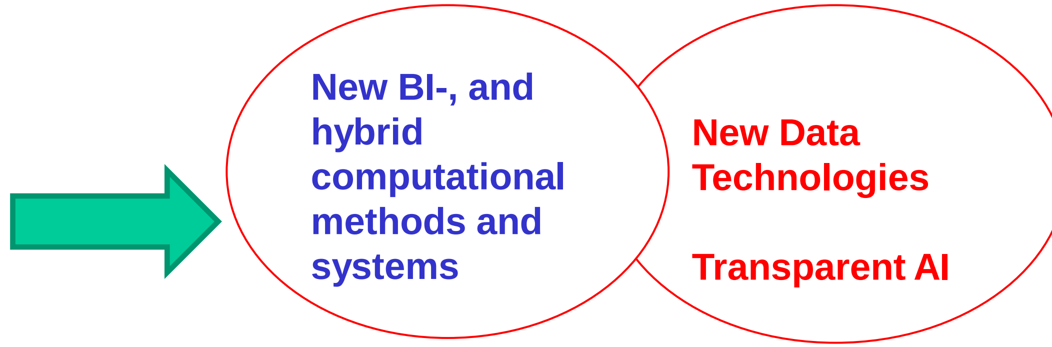
1. Self-organised, evolvable structure (no fixed number of layers/neurons, etc.)
2. *Event* based (asynchronous), fast, incremental, potentially "life-long" learning.
3. Temporal (spatio-temporal) associations learned.
4. Interpretability, e.g. TSK representation
5. Low computational power
6. Fault tolerance

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

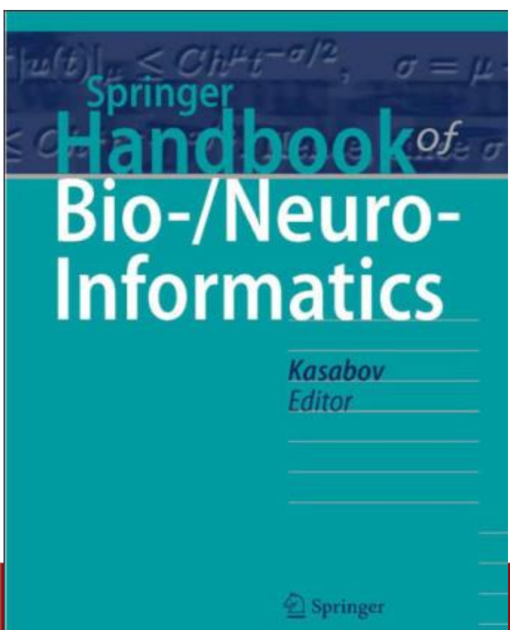
Future directions: BI-AI through BI-SNN architectures

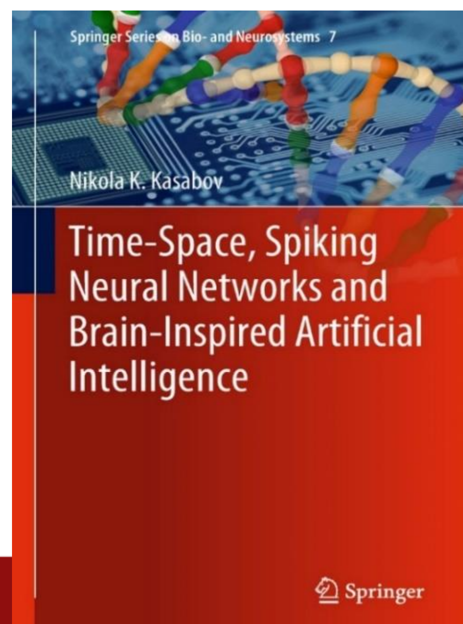




- Modelling emergence of symbolic representation
- Multimodal and multi-model SNN systems
- Quantum-inspired computation: Spikes as q-bits - in a superposition of 1/0

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



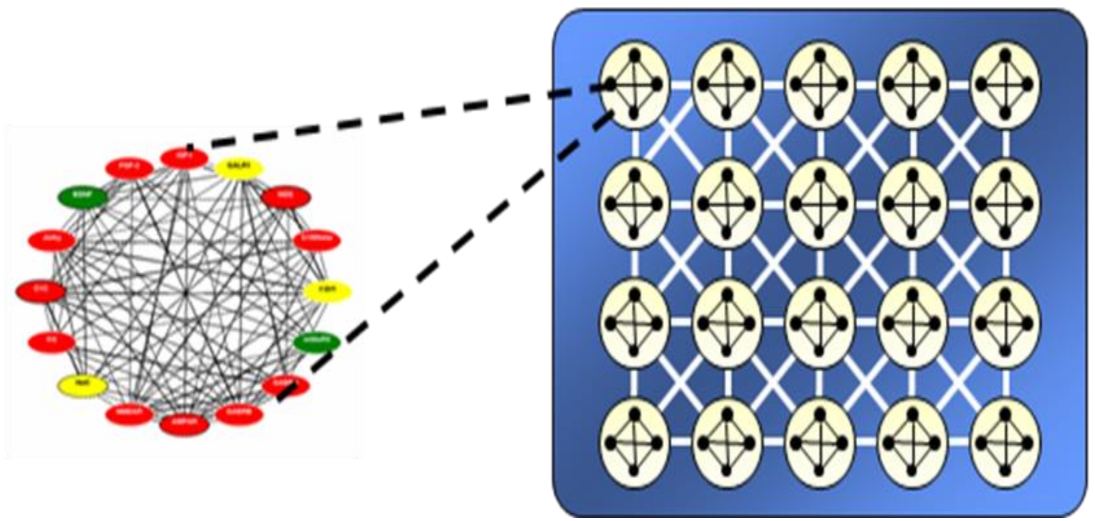


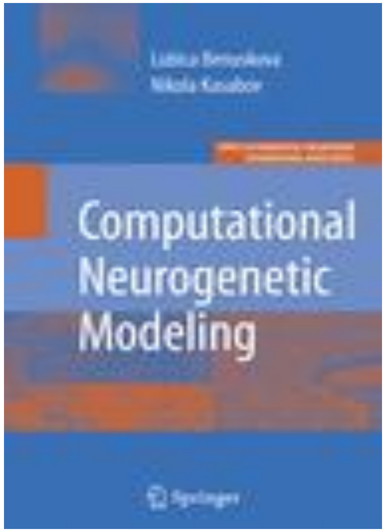
Future development:
Computational Neuro-Genetic Modelling (CNGM)

- 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.

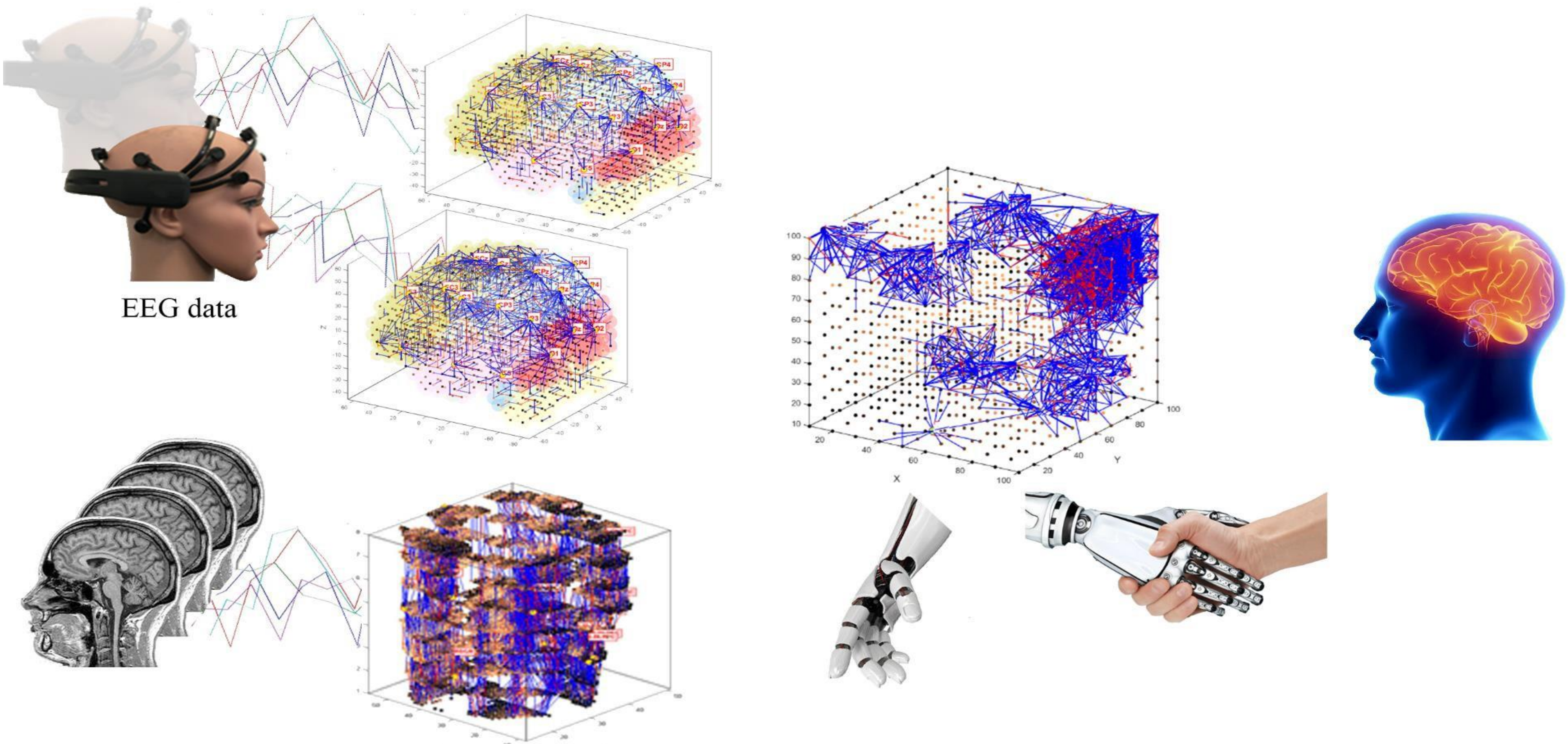
- Functions of neurons and neural networks are influenced by internal networks of interacting genes and proteins forming an abstract GRN model.
- The GRN and the SNN function at different time scales.





The goal: Knowledge-based human-machine interaction and symbiosis based on deep learning, knowledge representation and knowledge transfer with BI-SNN architectures

(www.darpa.mil/program/explainable-artificial-intelligence)



200+ application specific methods and systems based on NeuCube from 50+ countries

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