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Neuroinformatics, Neural Networks and Neurocomputers with some Applications in Neurosurgery

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THE EUROPEAN ASSOCIATION OF NEUROSURGICAL SOCIETIES

THE EANS TASK FORCE FOR EMERGING TECHNOLOGIES AND INNOVATIONS IN NEUROSURGERY (ETIN TASK FORCE)

Emerging Technologies and Innovations in Neurosurgery
EANS ETIN Task Force

The mission:
To investigate, promote and stimulate the advancement and implementation of new, emerging technologies and innovations in neurosurgery. To help neurosurgeons to stay at the upfront and remain leaders in the creative process of development of new devices and technologies, and their introduction in the everyday neurosurgical practice

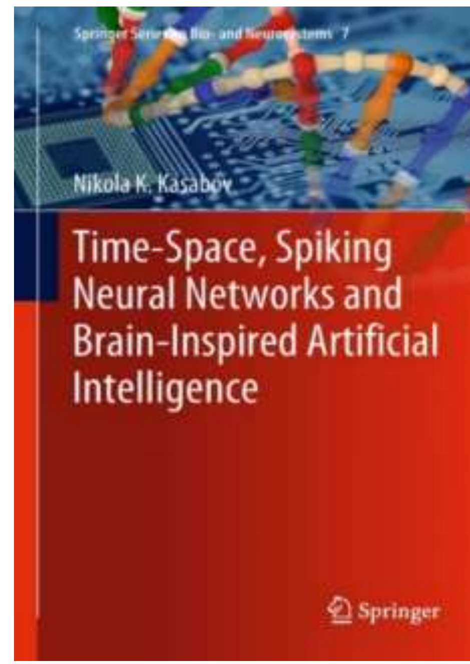
Key words:
Robotics, image guidance and navigation, artificial intelligence (AI), virtual reality (VR), augmented reality (AR), 3D printed technology, endoscopy, emerging technologies, technological innovations in Neurosurgery.

KEDRI

Abstract

1. AI in health and neurosurgery
2. Neuroinformatics
3. Neural networks (NN).
4. Brain-inspired spiking neural networks. NeuCube. *Neurocomputers.*
5. Application specific methods and systems
6. Discussions and future work

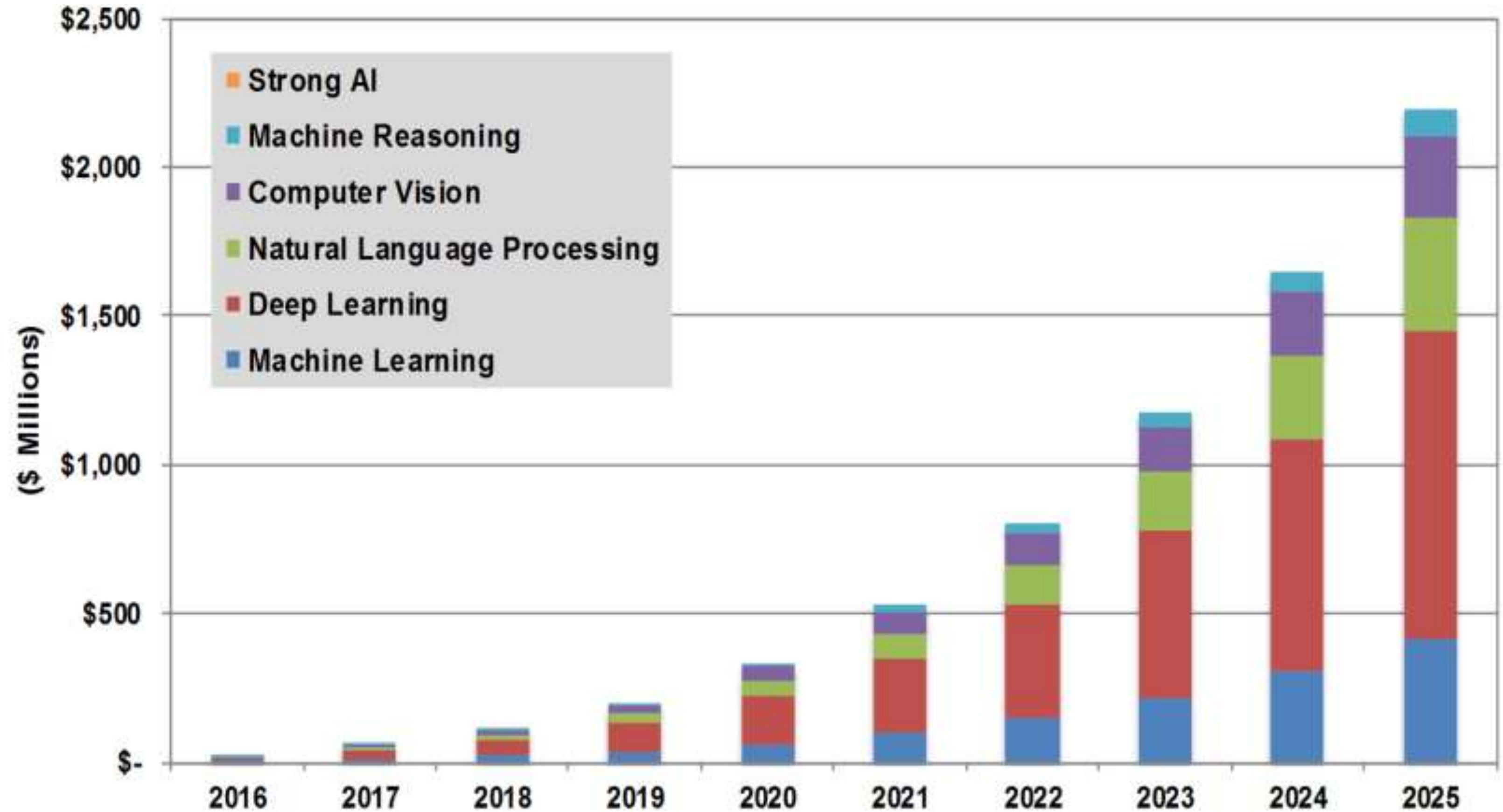
Reference:
N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019), https://www.springer.com/gp/book/9783662577134



1. AI in Health and Neurosurgery

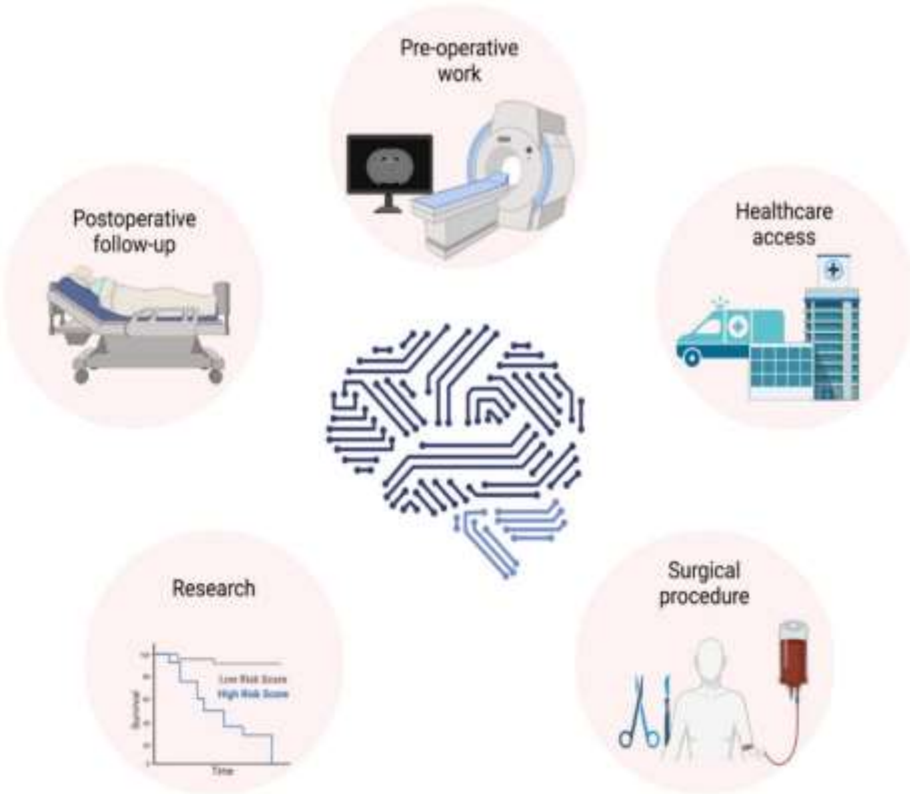
http://www.pwc.com/AI

Healthcare AI revenue by Machine Learning technologies - the World Market

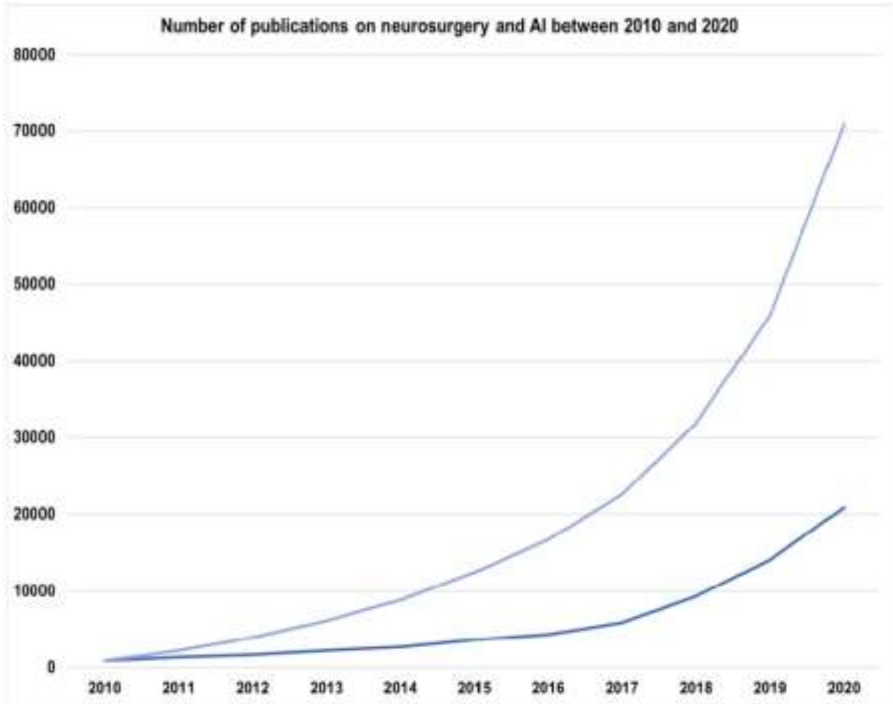


Tractica, White paper, 2017

AI in Neurosurgery



An overview of the role of AI in neurosurgery (from: Mohammad Mofatteh, Neurosurgery and artificial intelligence, https://doi.org/10.3934/Neuroscience.2021025) AIMS Neuroscience, 8(4): 477–495.



Absolute and the cumulative number of publications involved neurosurgery and artificial intelligence in their title or abstract over the past decade. The representative data was gathered from the database PubMed using neurosurgery OR neurological surgery OR brain surgery AND artificial intelligence OR machine learning OR deep learning search function in the title or abstract from 2010–2020

Why AI in Neurosurgery and what are the challenges?

Panesar, Sandip S MD, MSc; Kliot, Michel MD; Parrish, Rob MD, PhD; Fernandez-Miranda, Juan MD; Cagle, Yvonne MD; Britz, Gavin W MD. Promises and Perils of Artificial Intelligence in Neurosurgery. Neurosurgery 87(1):p 33-44, July 2020. | DOI: 10.1093/neuros/nyz471

Promises: AI techniques may permit rapid and detailed analysis of the large quantities of clinical data generated in modern healthcare settings, at a level that is otherwise impossible by humans. Subsequently, AI may enhance clinical practice by pushing the limits of diagnostics, clinical decision making, and prognostication.

Perils: Faulty, inadequately trained, or poorly understood algorithms may produce erroneous results, which may have wide-scale impact

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T. Forcht Dagi, Fred G. Barker, Jacob Glass, Machine Learning and Artificial Intelligence in Neurosurgery: Status, Prospects, and Challenges, Neurosurgery, www.neurosurgery-online.com

"Create a model that is as sophisticated as the problem requires – but not more so."
Craig MacDonald

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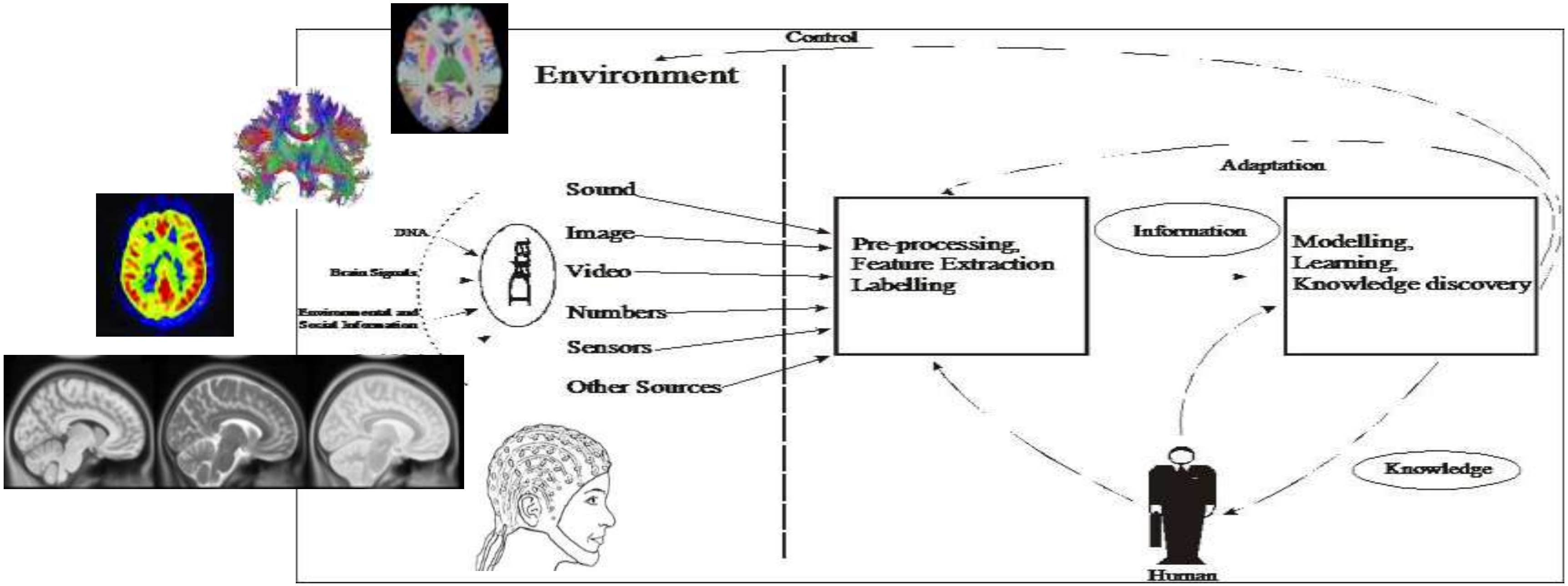
2. Neuroinformatics



Challenges:

1. Improved quality of data
2. Multiple modality (e.g. neuroimages, videos, signals, movement, cognitive).
3. Different types of data, e.g. vector based vs longitudinal; different time and space scales (EEG, fMRI)
4. Efficient learning of data (incremental, adaptive, life-long)
5. Predictive personalised modelling
6. Explainability

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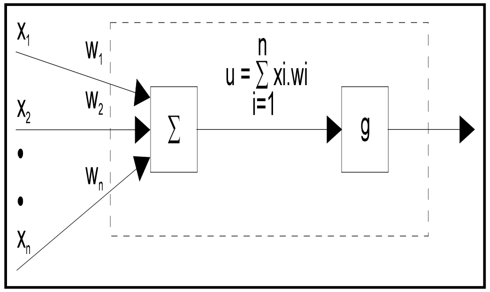
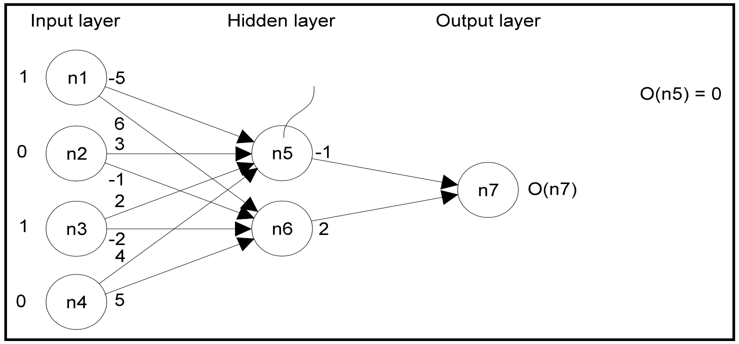
3. **Artificial Neural Networks**

- ANN are computational models that mimic the nervous system in its main function of adaptive learning and *generalisation.*
- ANN are *universal computational models*
- 1943, McCulloch and Pitts neuron
- 1962, Franc Rosenblatt – Perceptron
- 1965, B.Widrow, Adaline/Madeline
- 1971- 1986, Amari, Rumelhart, Werbos: Multilayer perceptron
- Many engineering applications
- Early NN: no adaptability and explainability

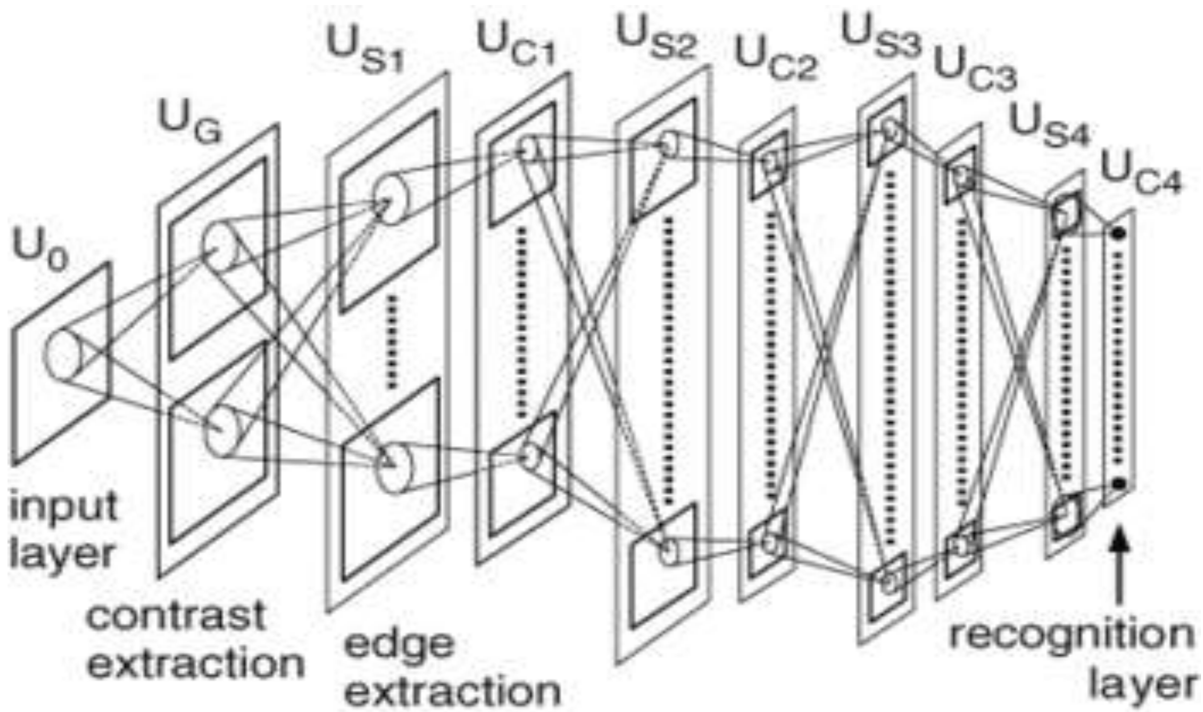




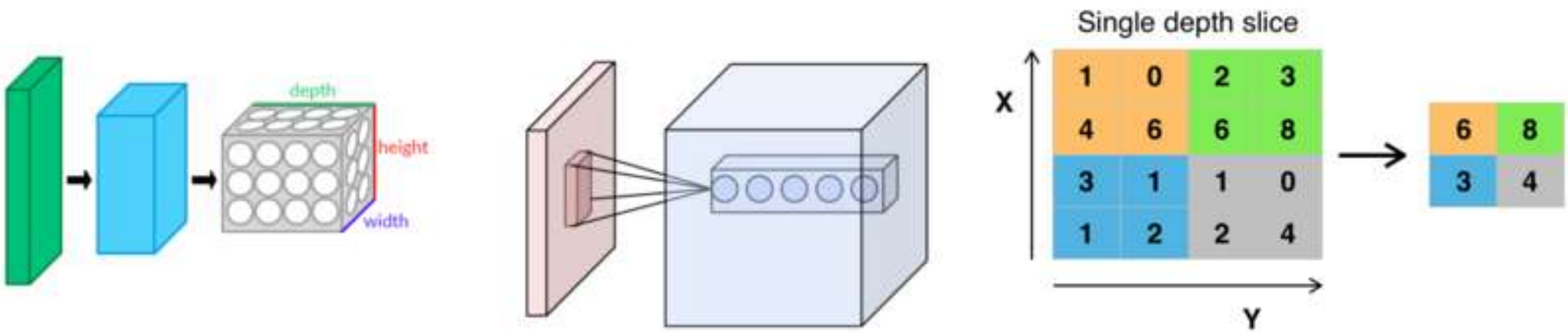
Early deep neural networks for computer vision

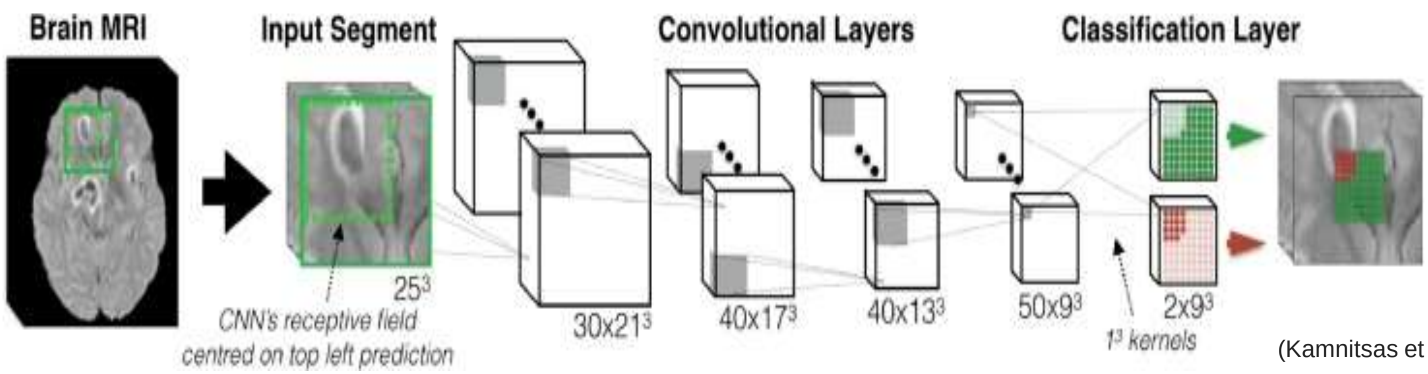
Spatial features are represented (learned) in different layers of neurons

Fukushima's Cognitron (1975) and Neocognitron (1980) for image processing



Deep Convolutional Neural Networks





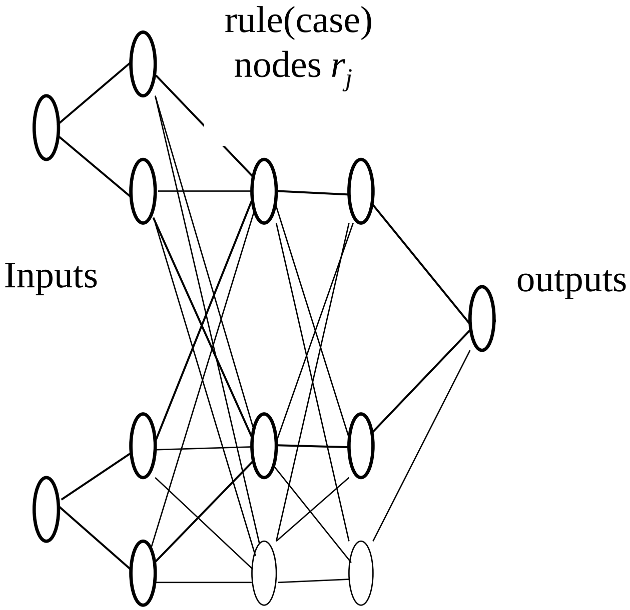
(Kamnitsas et al., 2017)

Deep NN are excellent for vector, frame- based data (e.g. image recognition), but not for spatio-temporal data and computer vision. There is no *time of asynchronous events* learned in the model. Difficult to adapt to new data and the structures are not flexible. How deep should they be? Who decides?

Adaptable and explainable evolving connectionist systems (ECOS) (Evolving fuzzy neural networks)

- EFuNN

DENFIS



IF Input 1 is High and Input 2 is Low THEN Output is Very High

N. Kasabov, EFuNN, IEEE Trans. SMC,2001.

N.Kasabov, Evolving connectionist systems, Springer, 2007.

Kasabov, N., and Song, Q., DENFIS: Dynamic Evolving Neural-Fuzzy Inference System and its Application for Time Series Prediction, IEEE Trans. on Fuzzy Systems, 2002.

24 Centuries after Aristotle' epistemology, now we can automate the process of rule extraction and knowledge discovery from data!

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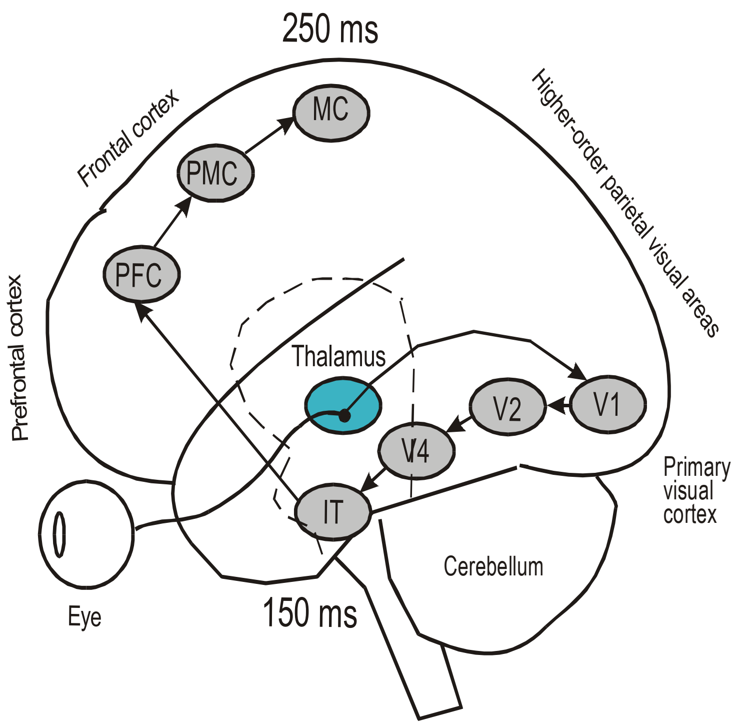
4. **Brain-inspired spiking neural networks. NeuCube. Neurocomputers**

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



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

Three, mutually interacting, memory types:

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

Temporal data at different time scales:

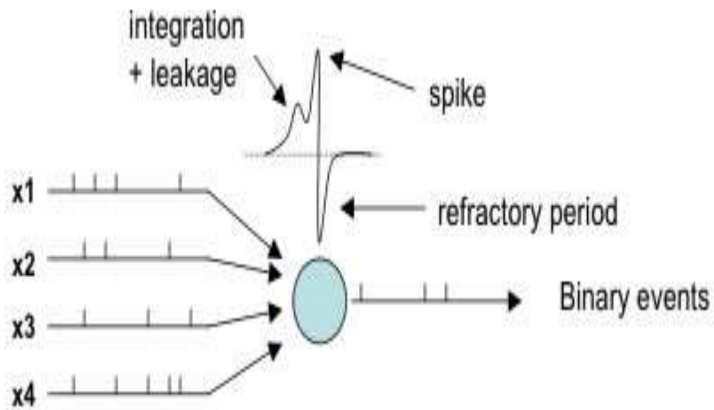
- Nanoseconds: quantum processes;
- Milliseconds: spiking activity;
- Minutes: gene expressions;
- Hours: learning in synapses;
- Many years: evolution of genes.

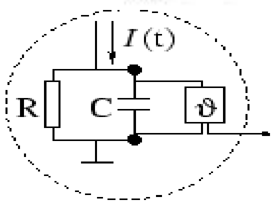
Knowledge is represented as deep spatio-temporal patterns that can evolve/adapt over time.

The challenge for AI:

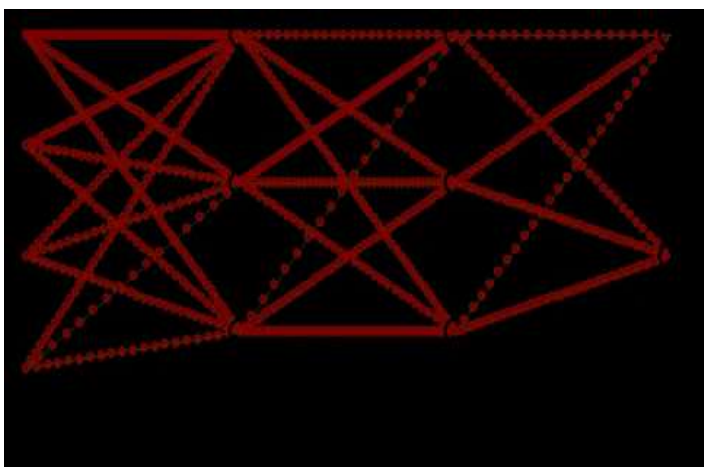
Can we use these principles to build AI systems that can learn incrementally and possibly in a life-long learning mode and can be interpreted as knowledge discovery at any phase of their learning?

Spiking Neural Networks





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



Information processing principles in SNN

- Trains of spikes
- Time, frequency and space
- Synchronisation and stochasticity
- Spike-time and spike-rate information

Spiking neural networks (SNN)

- Leaky Integrate-and-fire
- Izhikevich models
- Probabilistic model
- Neurogenetic model

They offer the potential for:

- Spatio-temporal data processing
- Bridging higher level functions and "lower" level genetics
- Integration of modalities

SNN opened the field of brain-inspired computation and the creation of neurcomputers .

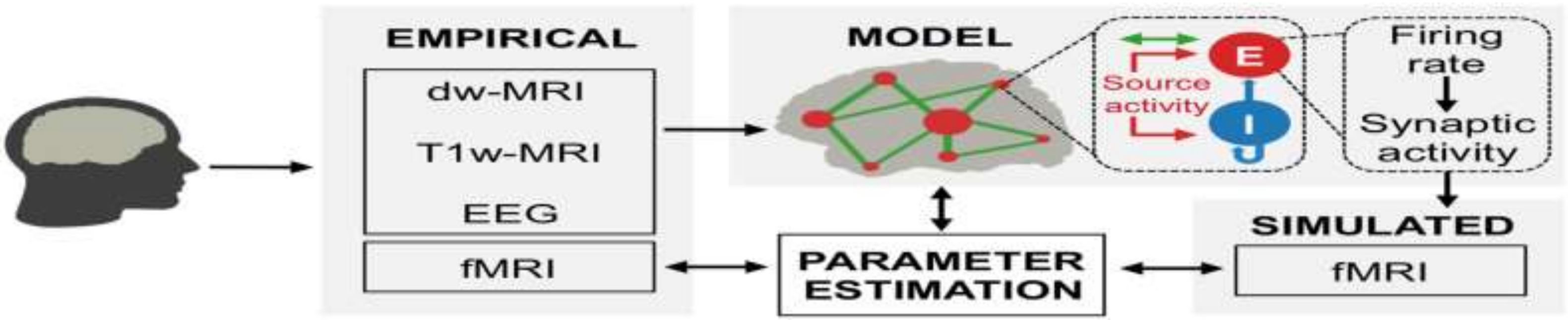
"*The goal of brain-inspired computing is to deliver a scalable neural network substrate while approaching fundamental limits of time, space, and energy,*" IBM Fellow **Dharmendra Modha**, chief scientist of Brain-inspired Computing at IBM Research,

Brain modelling and brain-inspired systems

(1) Brain-modelling systems: detailed analysis of brain functions and their computational modelling

- Horizon 2020 Blue Brain Project
- TheVirtual Brain: https://docs.thevirtualbrain.org/index.html

TheVirtualBrain is a framework for the simulation of the dynamics of large-scale brain networks with biologically realistic connectivity.

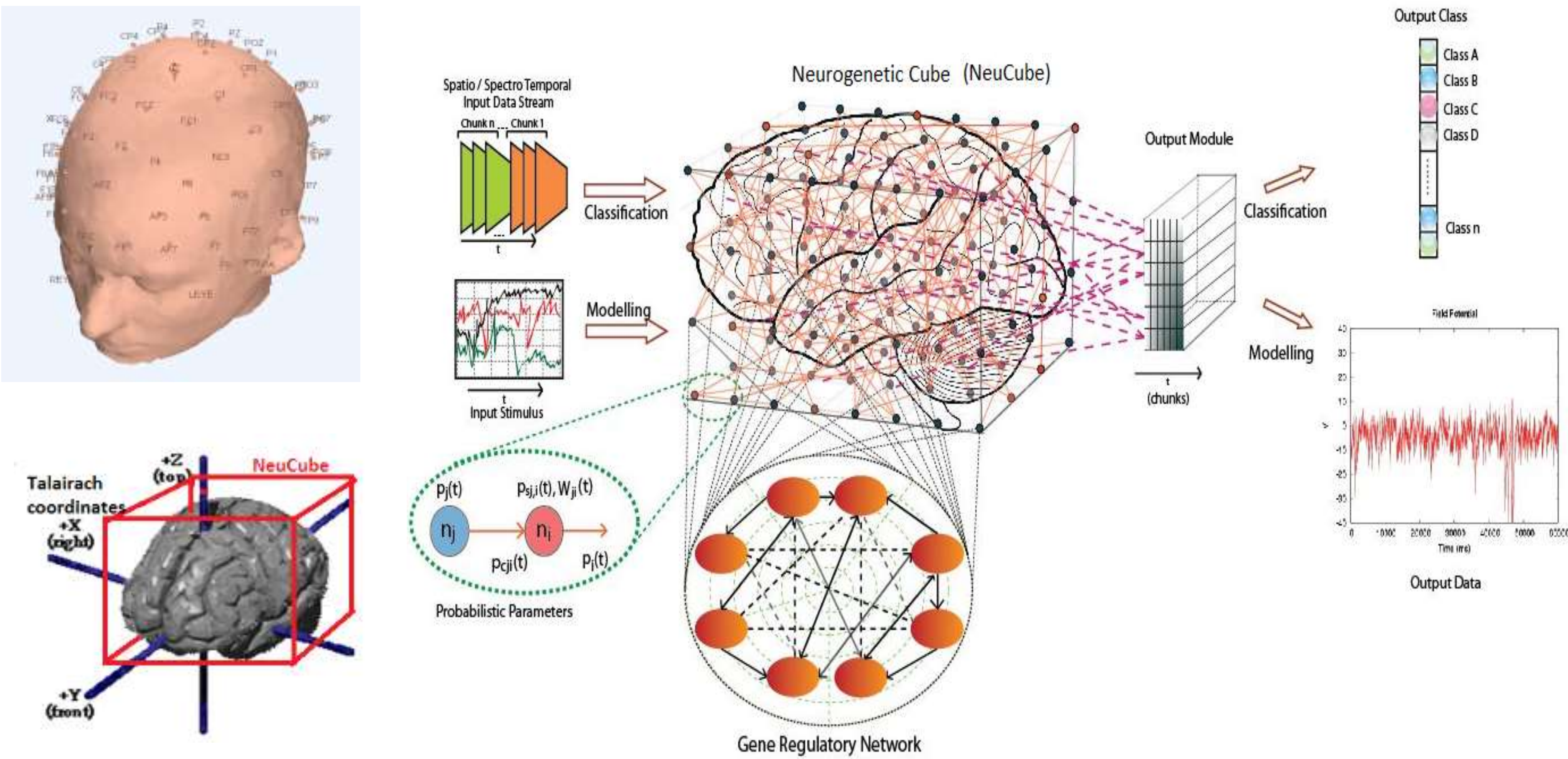


Michael Schirner, Anthony Randal McIntosh, Viktor Jirsa, Gustavo Deco, Petra Ritter, Inferring multi-scale neural mechanisms with brain network modelling, https://www.elifesciences.org,

(2) Brain-inspired data analytics: using brain principles to build models of brain data that can be used to understand back brain functions (reverse engineering)

- For computer vision (DVS, NeoCognitron) (Keshab k. Parhi, Nanda k. Unnikrishnan, Brain-Inspired Computing: Models and Architectures,
- For spatio-temporal brain data (NeuCube)

The NeuCube brain-inspired SNN architecture for spatio-temporal brain-data



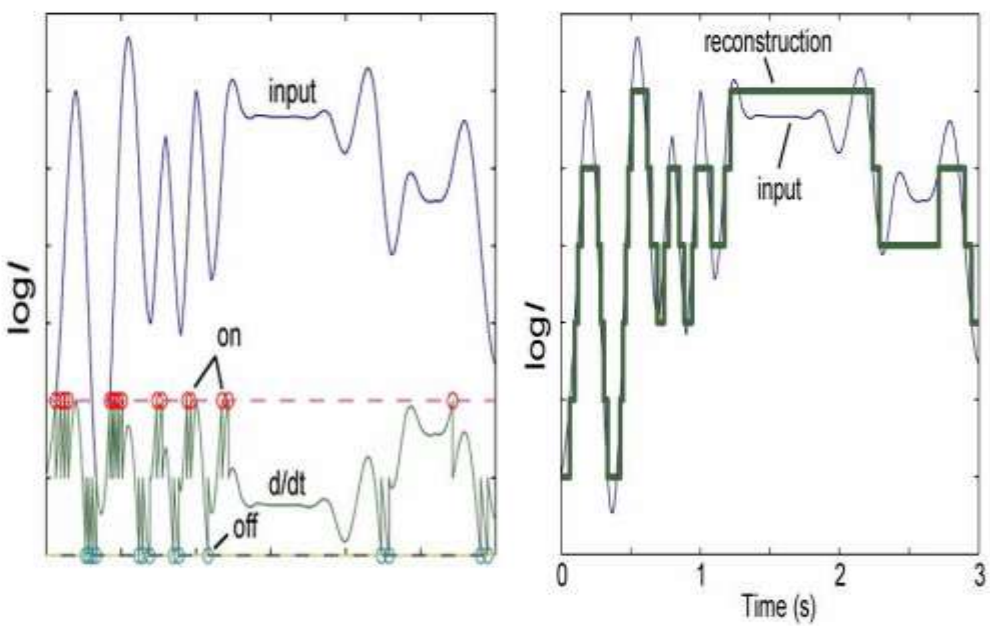
Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

Spike encoding methods

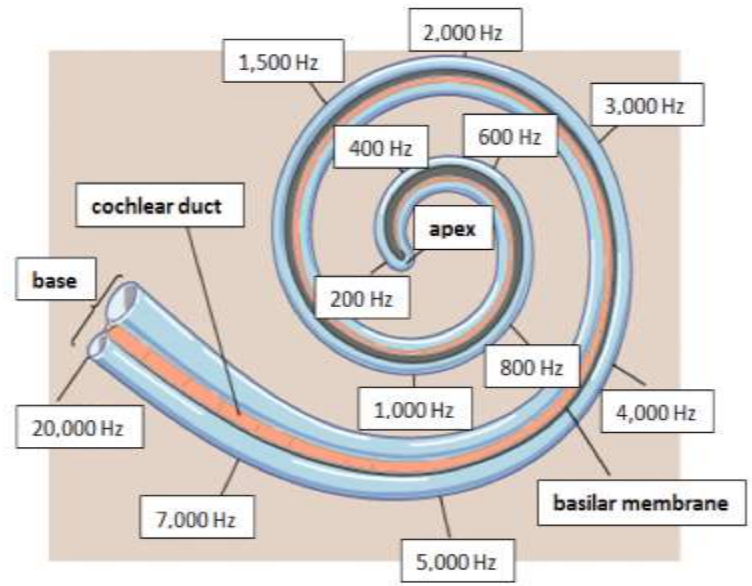
A spike is generated only if a change in the input data occurs beyond a threshold

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

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



Threshold-based encoding, retinotopic (INI/ETH Zurich)



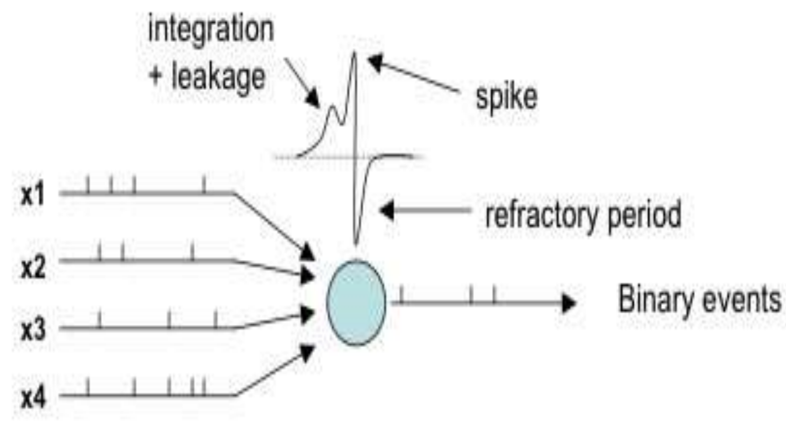
Tonotopic organization of the cochlea

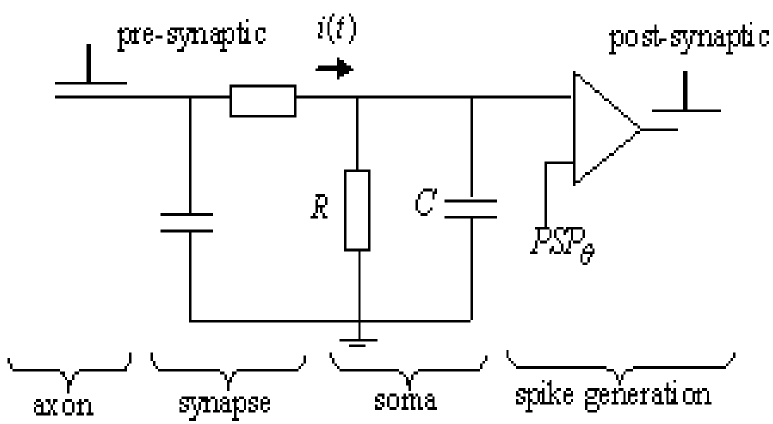
https://sites.google.com/site/jayanthinyswebite

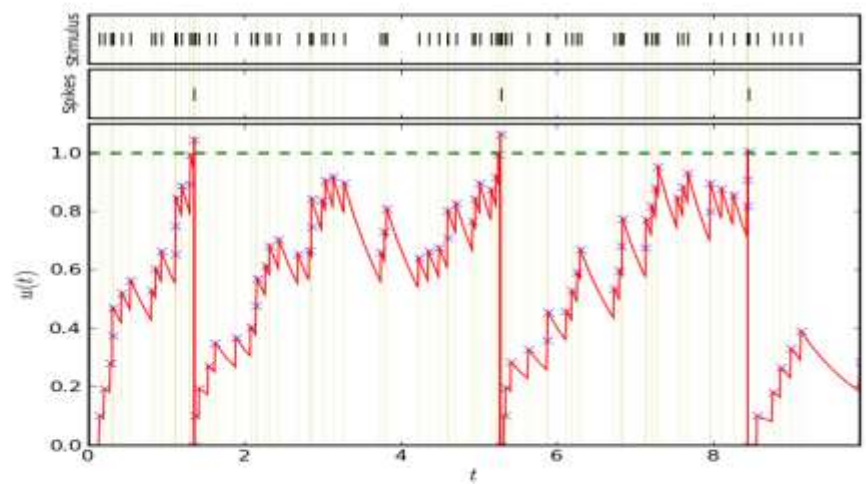
Spiking neuron models

Models of a spiking neurons and SNN

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



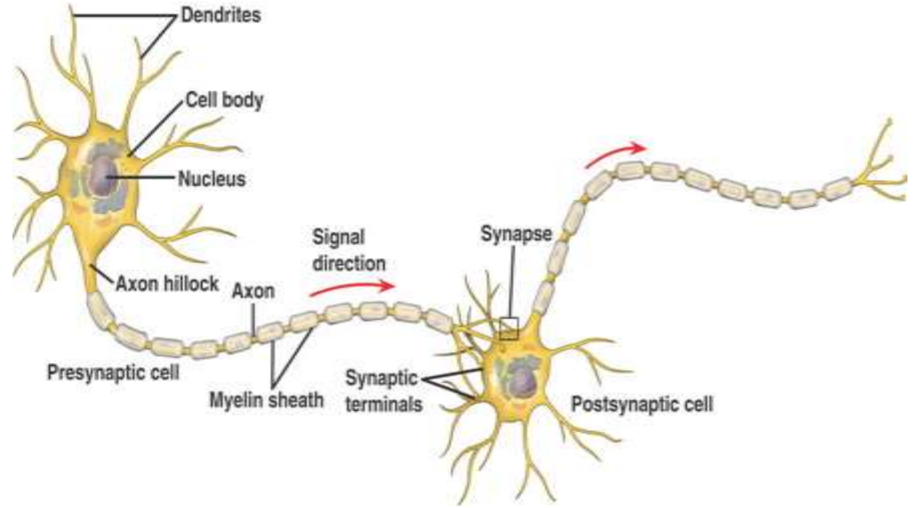




Methods for unsupervised learning in SNN

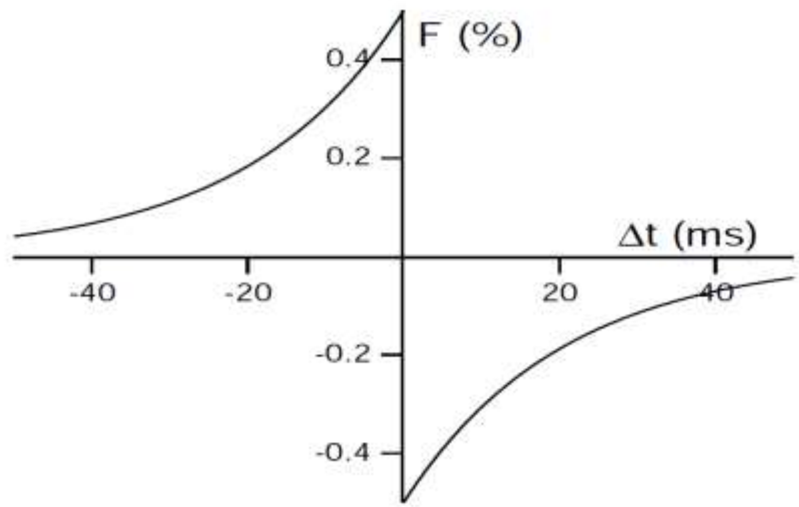
Spike-Time Dependent Plasticity (STDP)
(Abbott and Nelson, 2000).

- 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



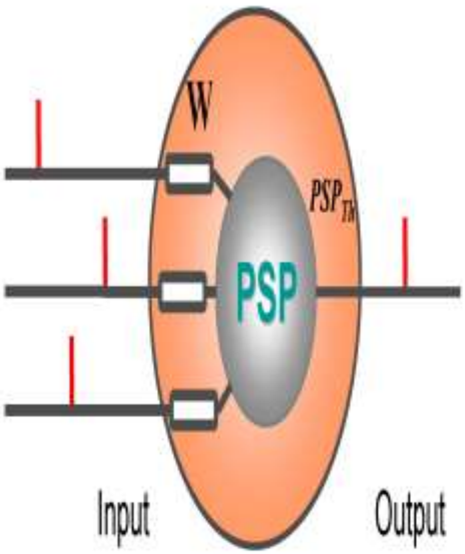
Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD:

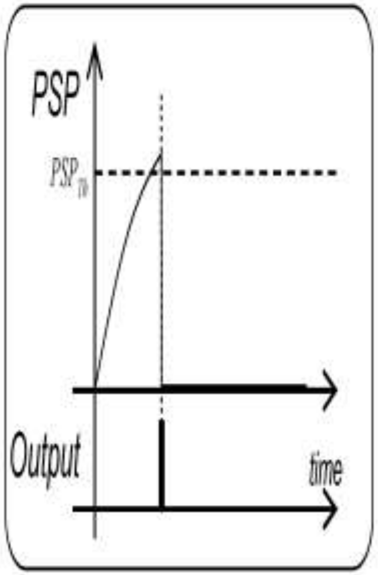
Δt=tpre -tpost



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

PSP_{Th}=C. PSPmax (T) (C <1 for early spiking)

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

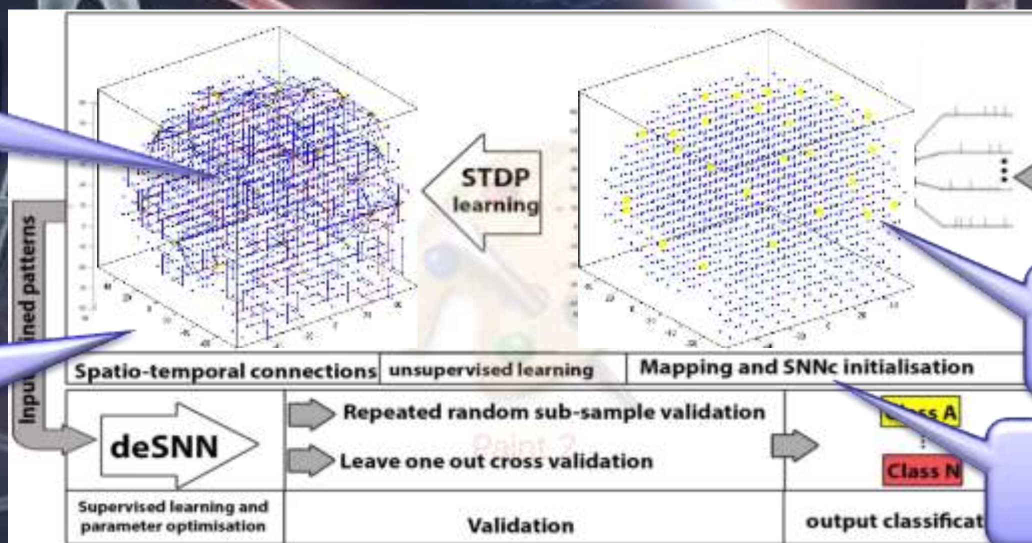
Dynamic Evolving SNN (deSNN)

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.

Deep learning in NeuCube

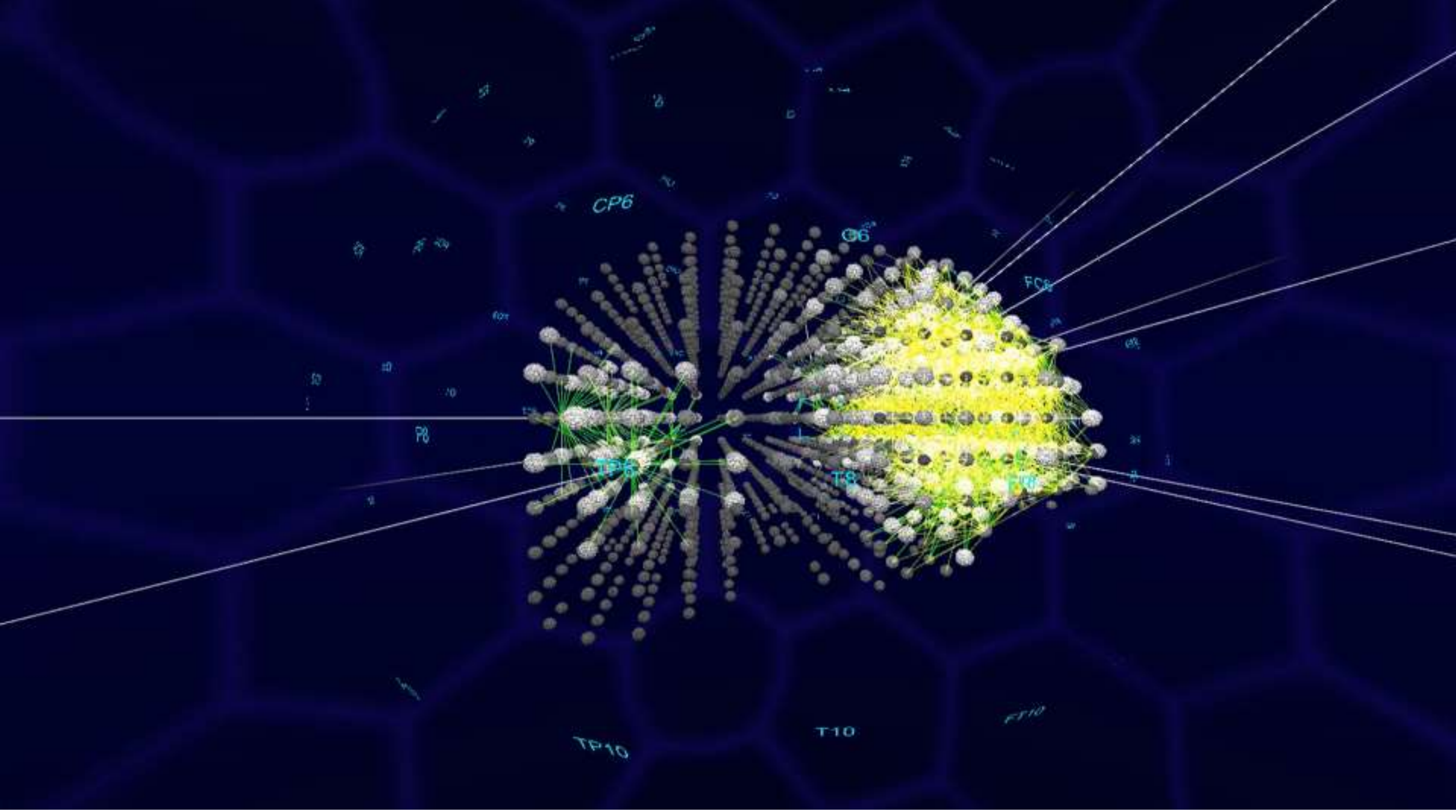
Creation of Neuron Connections During The Learning

The More Spike Transmission, The More Connections Created



Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning



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 (best paper award by the Neural Network journal)

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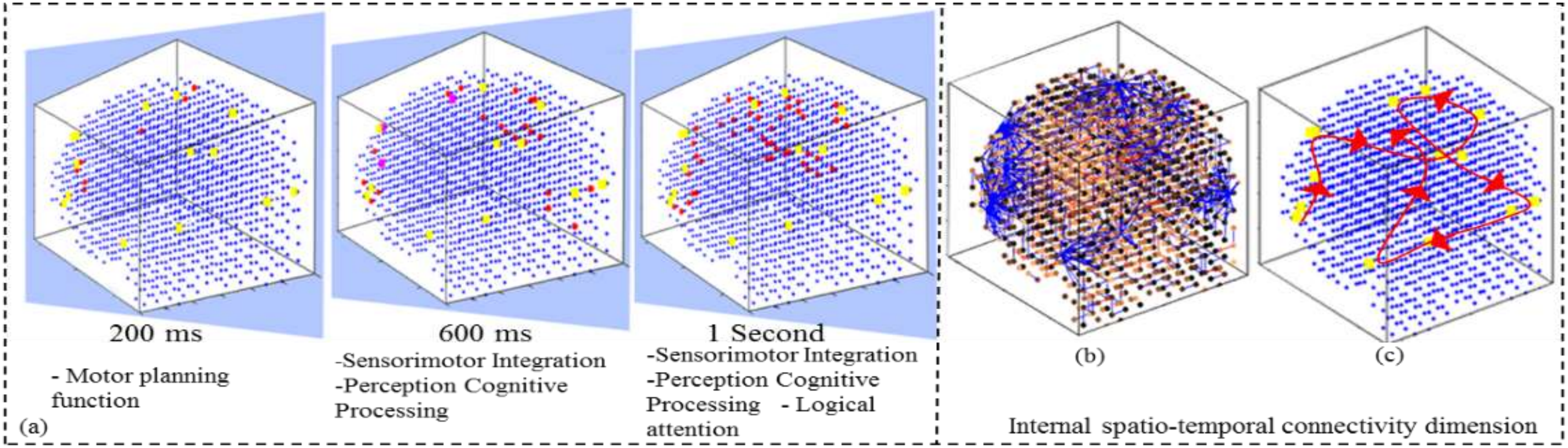
Example

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 a spatio-temporal rule.



IF (a person is moving a hand up)

THEN (the following neurnal areas representing 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

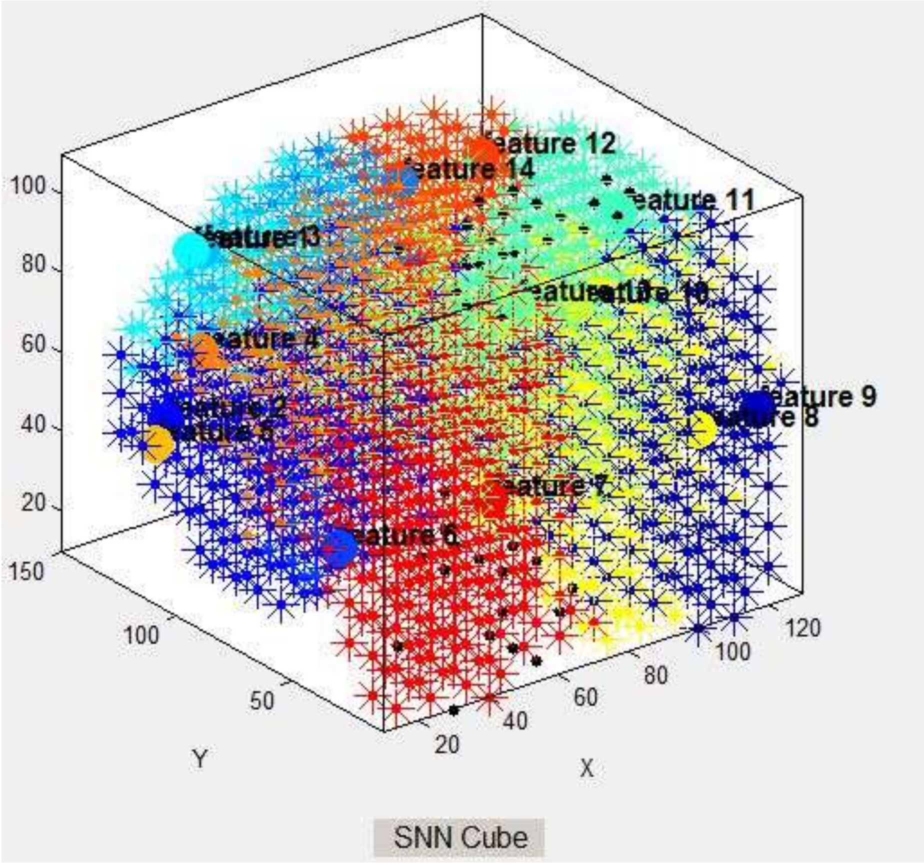
AND E3: Perception, in the Perception Cognitive brain area, time T3

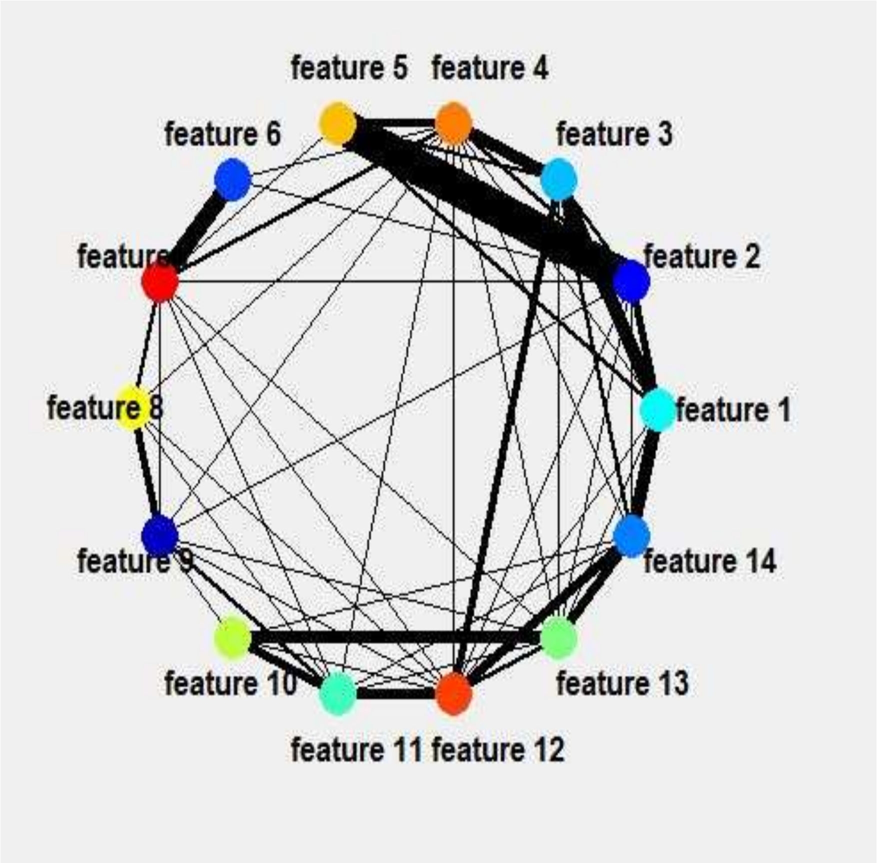
AND E4: Attention, in the Logical Attention brain area, time T4.

Capturing time-space knowledge as information exchange between clusters of neurons representing brain areas

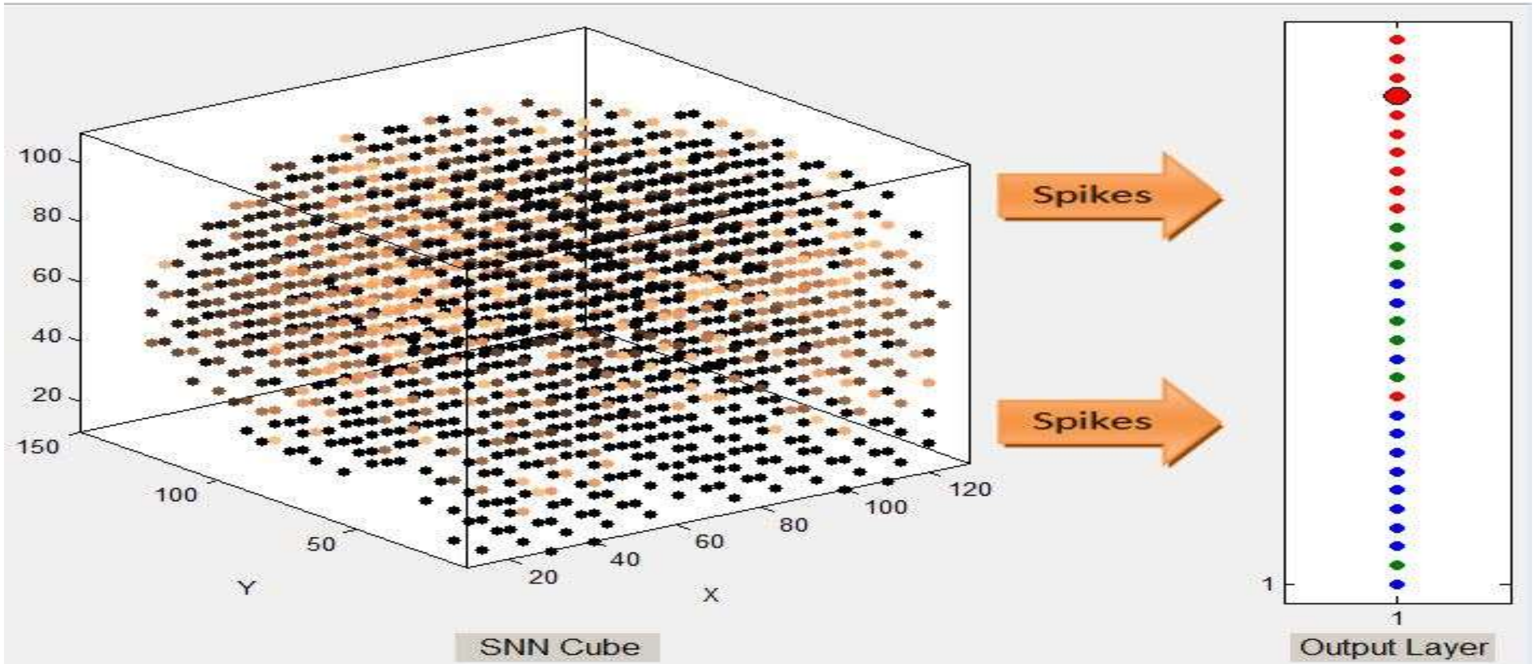
- Clusters of highly connected neurons to input neurons;
- Clusters of spiking activity spread from input neurons ;

- 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 a spatio-temporal rule associating Cube activities with outputs (actions)

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).

NeuCube development environment for SNN system design

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Neurocomputers: 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.

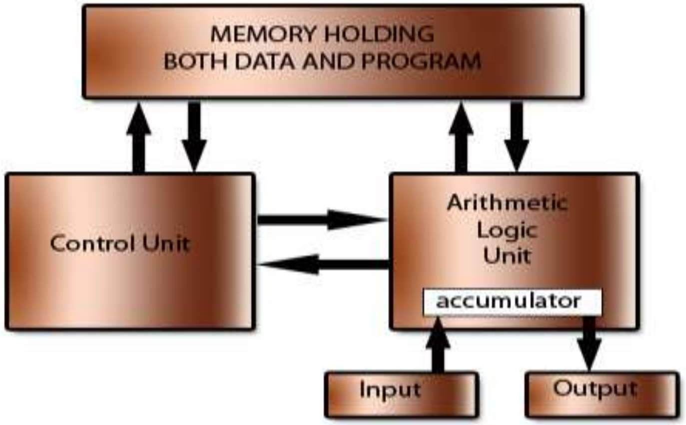
- A Neuromorphic architecture integrates the data, the programme and the computation in a SNN structure, similar to how the brain works; uses *spikes* (bits at times).

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

A SNN application system can be implemented as:

- von Neumann architecture;
- Neuromorphic architecture;
- Quantum computer.

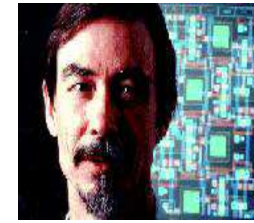
The Von Neumann or Stored Program architecture



(c) www.teach-ict.com

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 systems (Neurocomputers)



Massively parallel, high speed, low power consumption/

Carver Mead (1989): A hardware model of an IF neuron:
The Axon-Hillock circuit.

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

INI Zurich SNN chips (Giacomo Indiveri)

Silicon retina (the DVS) and silicon cochlea (ETH, Zurich, Toby Delbruck))

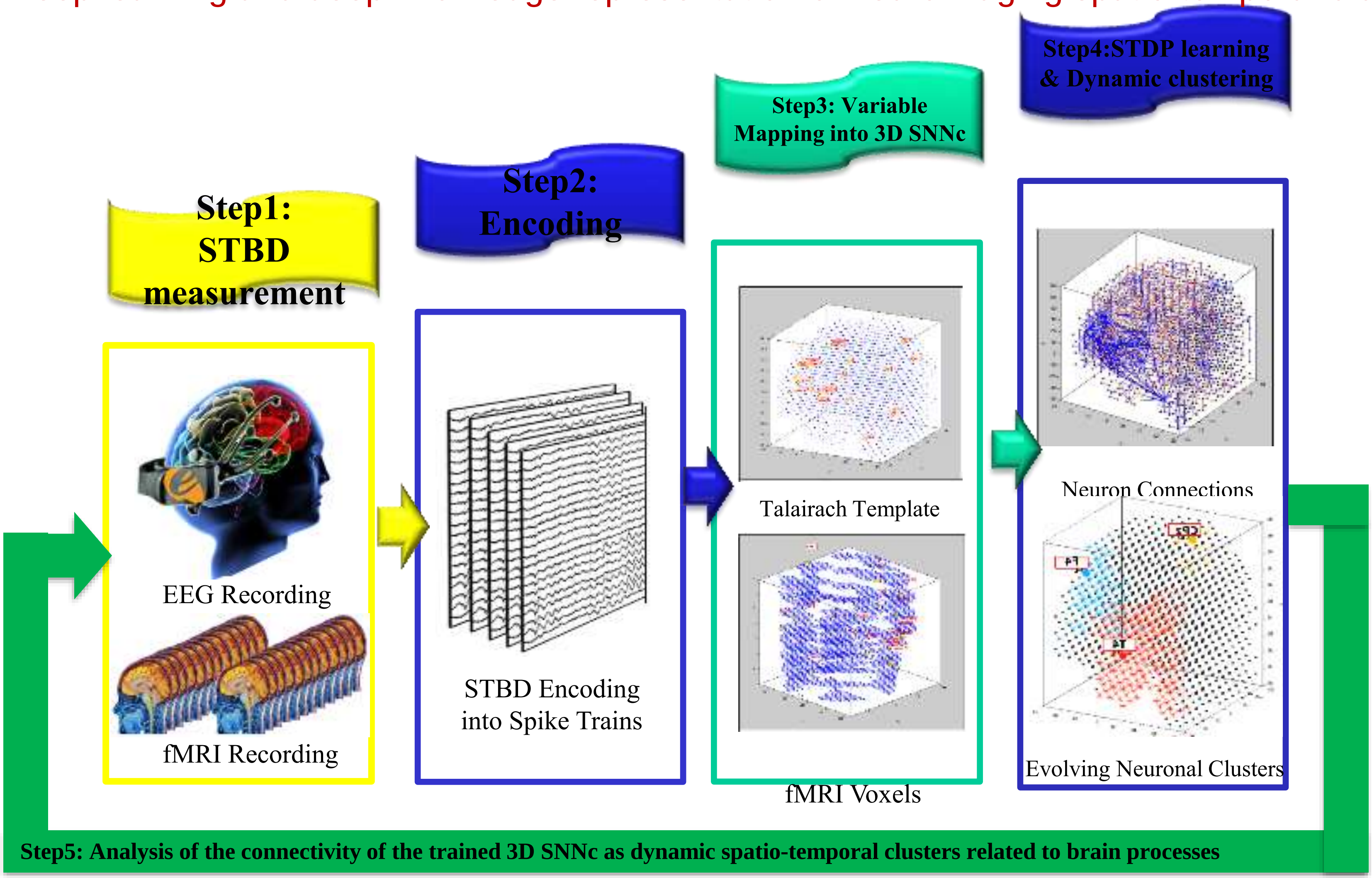
The IBM True North (D.Modha et al, 2016): 1mln neurons and 1 billion of synapses

FPGA SNN realisations (McGinnity, Ulster and NTU)

INTEL Lohia (128 cores, each for 1,024 spiking neurons) .

5. Application specific methods and systems

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

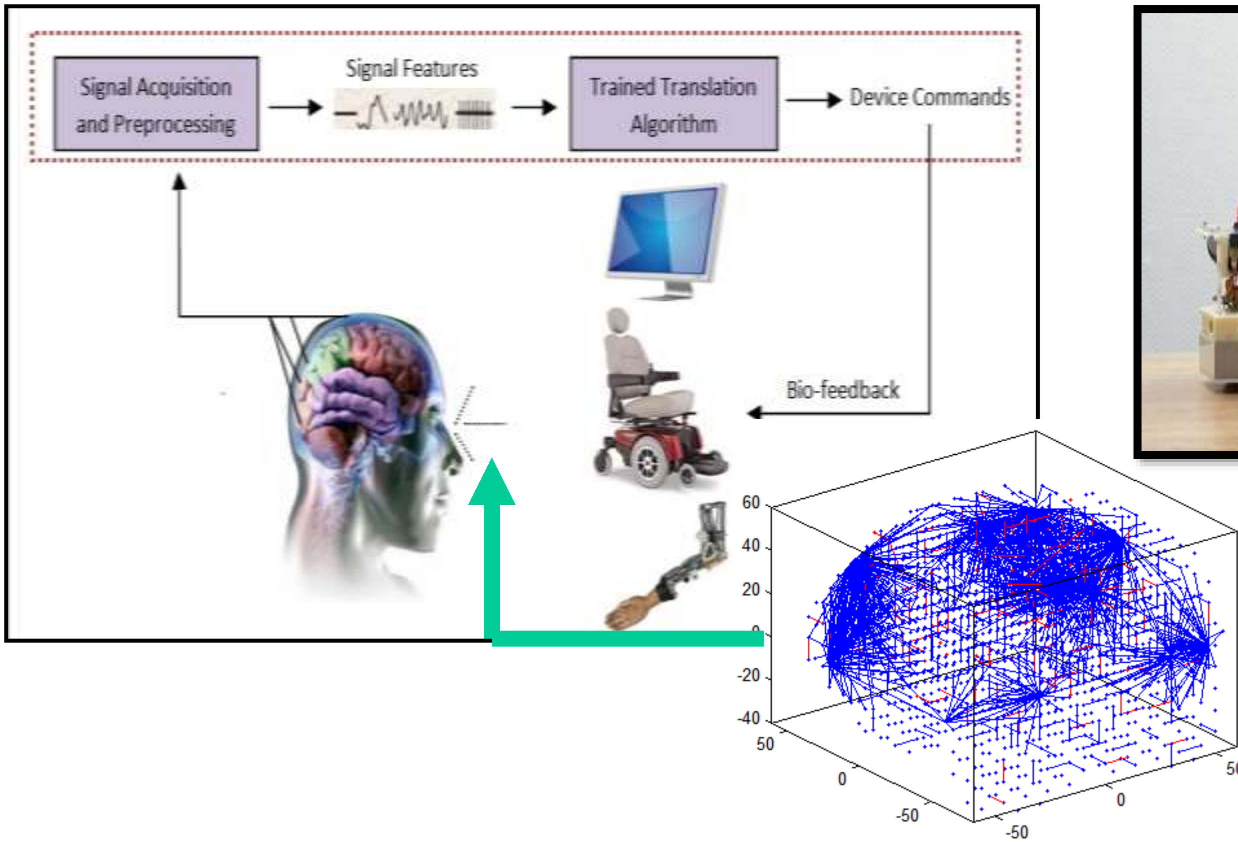


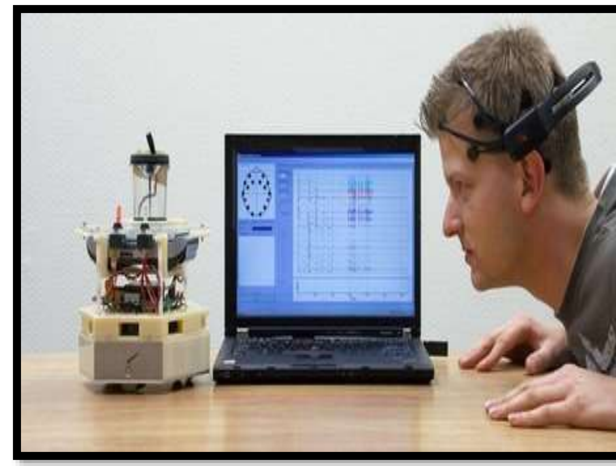
*Z.*Doborjeh, N. Kasabov, M. Doborjeh & Alexander Sumich**,** Modelling Peri-Perceptual Brain Processes in a Deep Learning Spiking Neural Network Architecture, ***Nature,*** Scientific REPORTS | (2018) 8:8912 | DOI:10.1038/s41598-018-27169-8; https://www.nature.com/articles/s41598-018-27169-8

Brain Machine Interfaces using Brain-Inspired SNN

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

BI-BMI are designed using a brain template.





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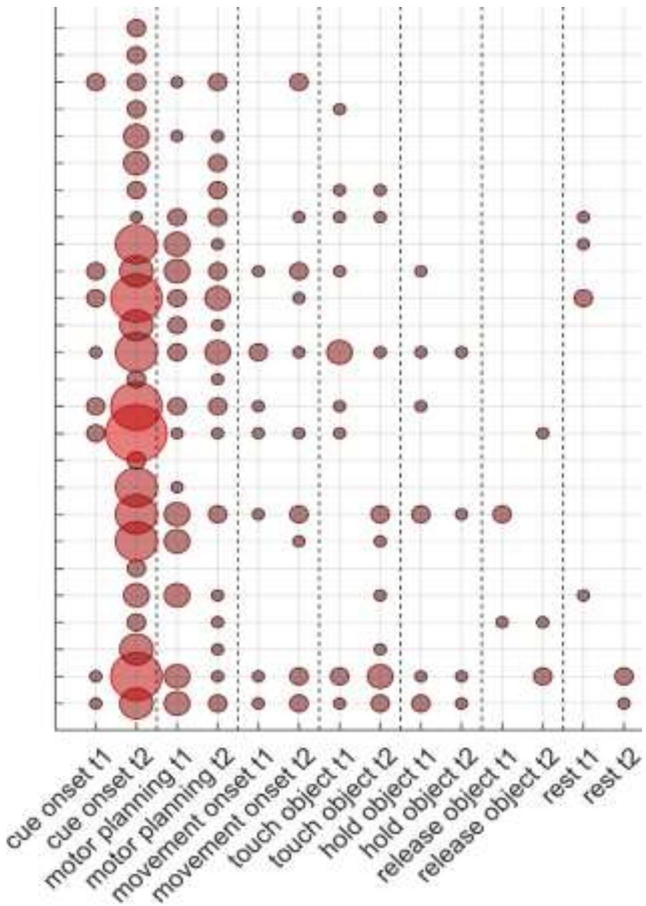
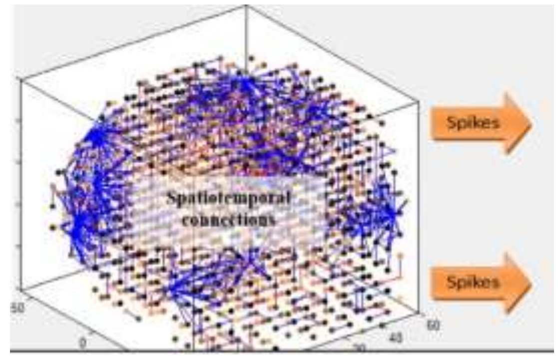
Extracting Time-Space Rules (TSR) from a trained NeuCube using EEG data for the GAL task

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





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

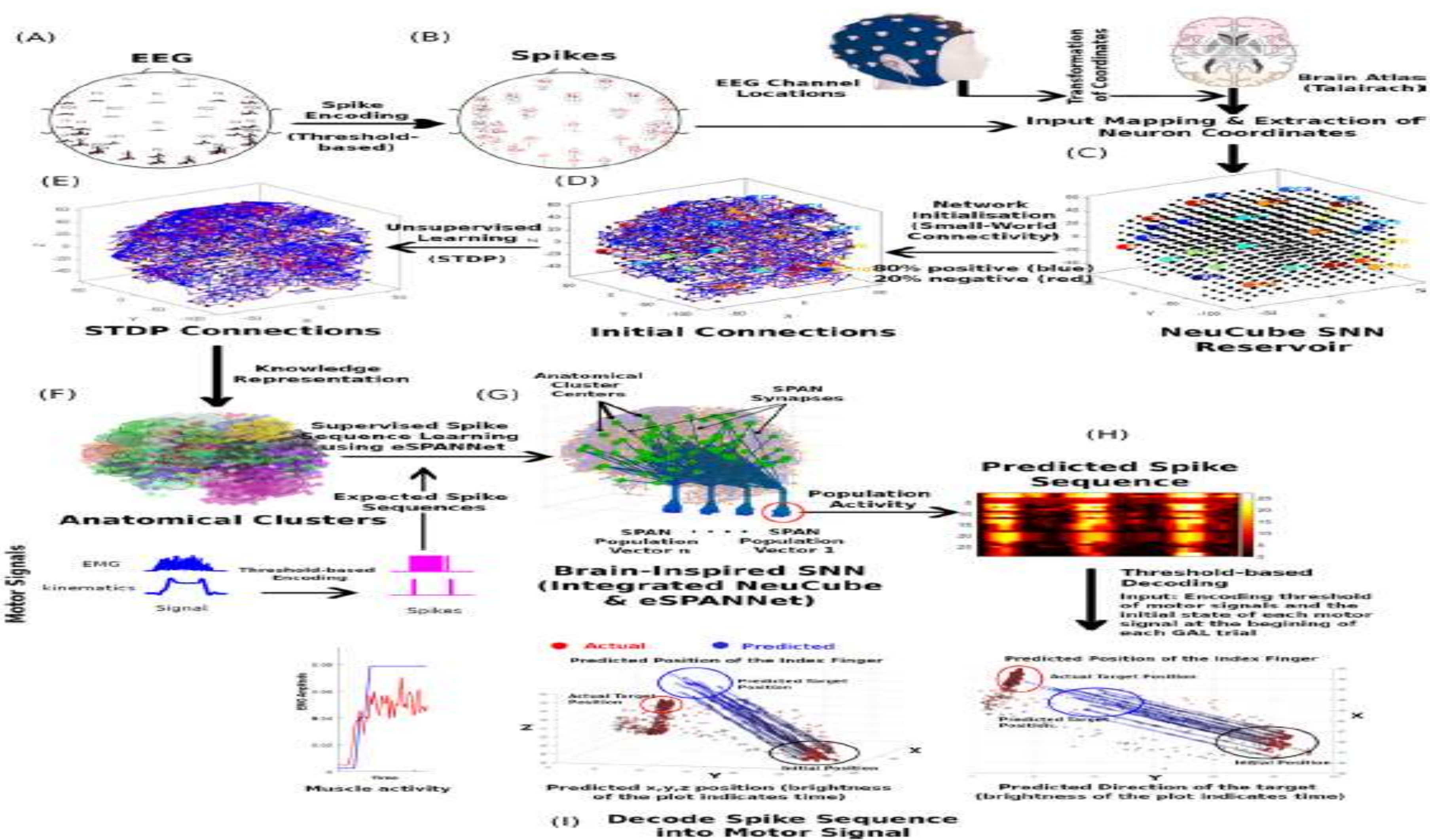
where Si = {Posterior Lobe, Temporal Lobe, Limbic Lobe, Frontal Lobe, Anterior Lobe, Occipital Lobe, Midbrain, Parietal Lobe}

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

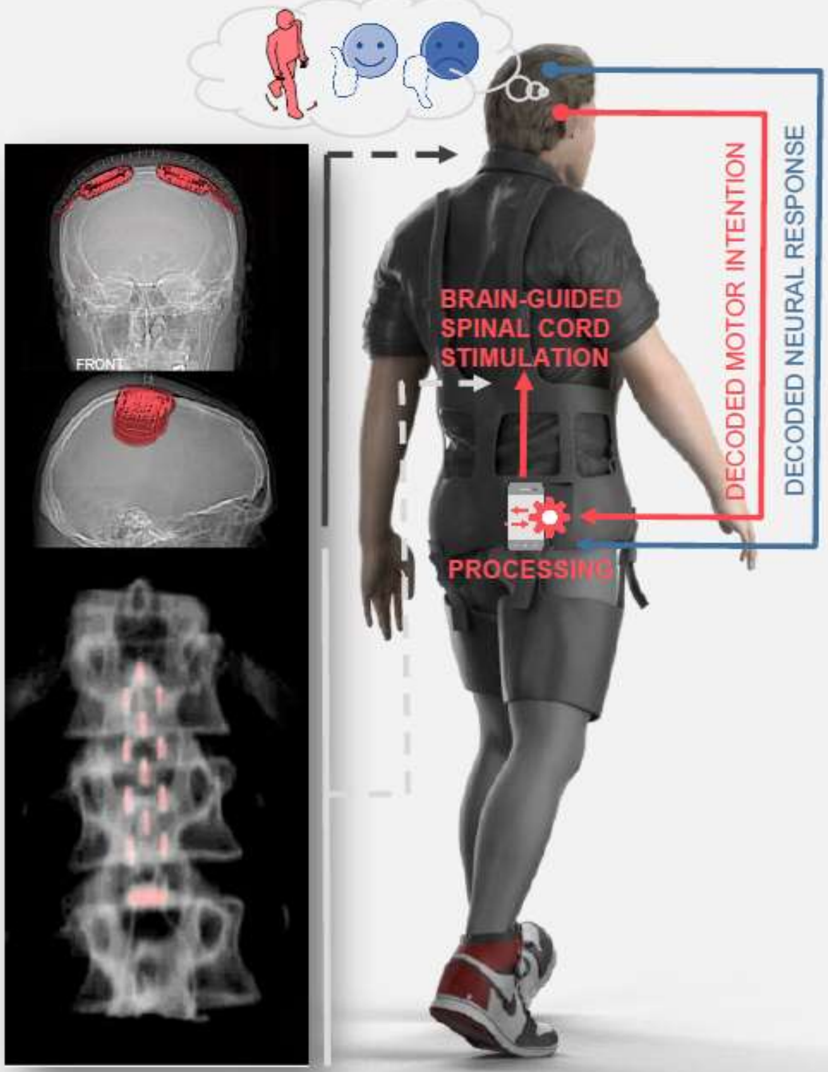
K.Kumarasinghe, N.Kasabov, D.Taylor, Deep Learning and Deep Knowledge Representation in Spiking Neural Networks for Brain-Computer Interfaces, Neural Networks, vol.121 (2020),169-185, doi: https://doi.org/10.1016/j.neunet.2019.08.029.

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 Neuroscience for 2021)



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

NEMO-BMI, HORIZON-EIC-2021-PATHFINDERCHALLENGES-01-02
France (CEA, Grenoble), the Netherlands (ONWARD), Switzerland (EPFL), Bulgaria (IICT/BAS)

NEMO-BMI

Our IICT/BAS/BG team

Team leaders

Prof. Petia Koprinkova-Hristova

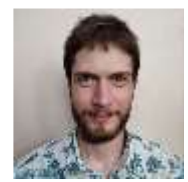
Prof. Nikola Kasabov

Researchers

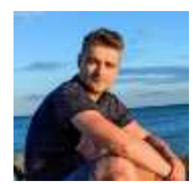
Assistant Simona Nedelcheva

PhD student or Postdoc

Programmers



Dimitar Penkov

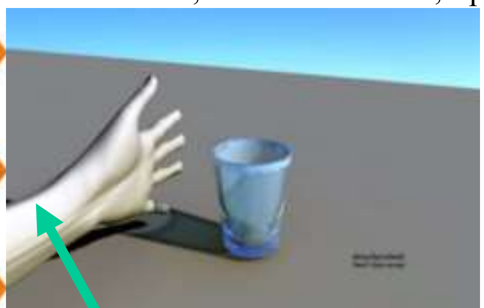


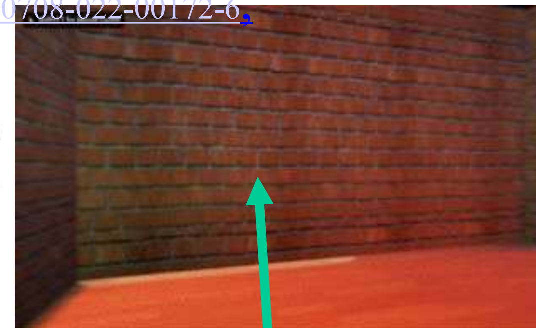
Svetlozar Yordanov

Modelling brain EEG signals while working with a VR/AR. Cybersickness

Yang AHX, Kasabov NK, Cakmak YO. Prediction and Detection of Virtual Reality induced Cybersickness: A Spiking Neural Network Approach Using Spatiotemporal EEG Brain Data and Heart Rate Variability. Research Square; 2022. DOI: 10.21203/rs.3.rs-2383481/v1, Brain Informatics, Springer-Nature, 2023

Alexander Hui Xiang Yang, Nikola Kasabov and Yusuf Ozgur Cakmak, Machine Learning Methods for the Study of Cybersickness: A Systematic Review, Brain Informatics, Springer-Nature, 9:24, 2022, https://doi.org/10.1186/s40708-022-00172-6,

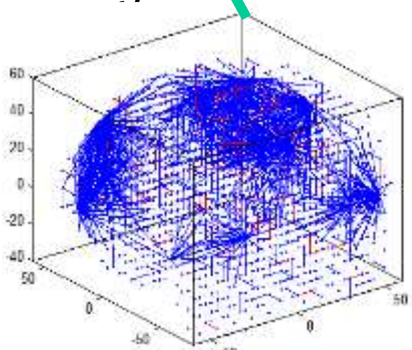


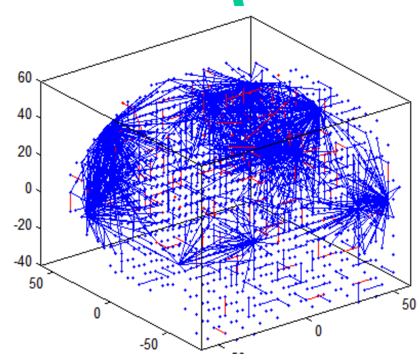


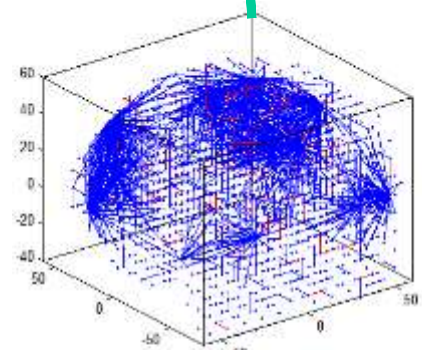
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.

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.



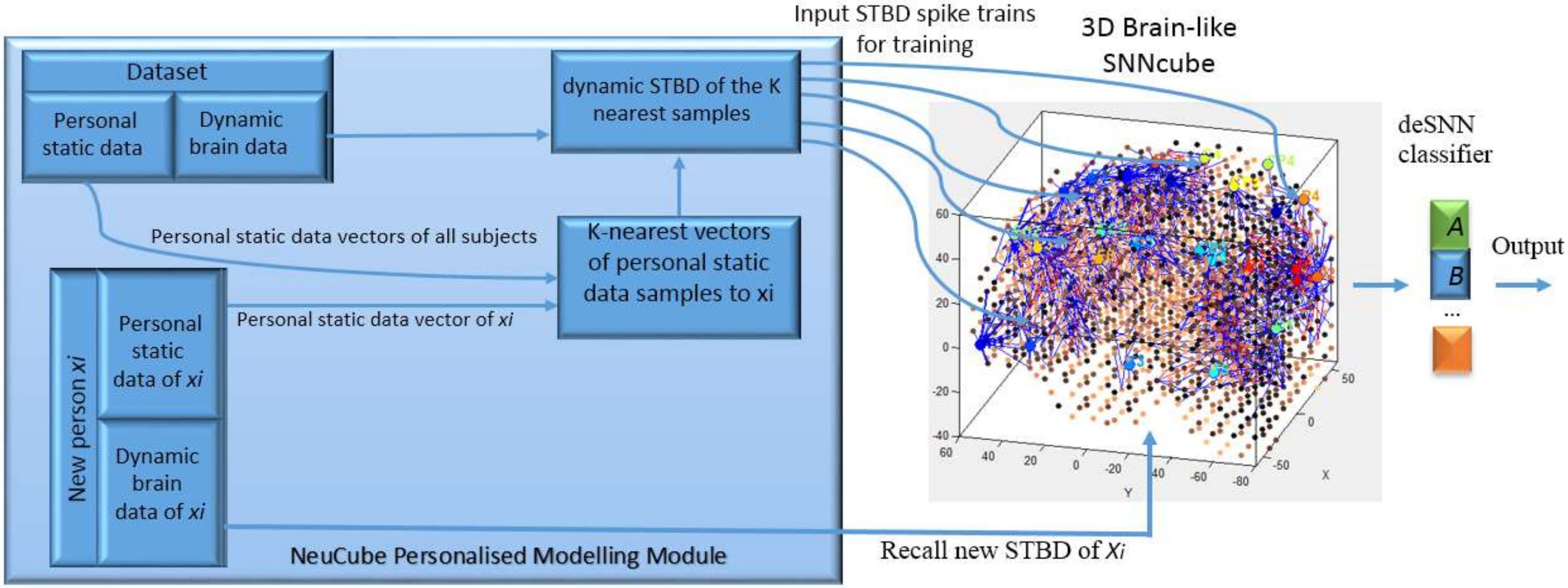




Personalised modelling for predicting response to treatment of drug addicts
(Class M - who take medication; class OP – who do not take medication)

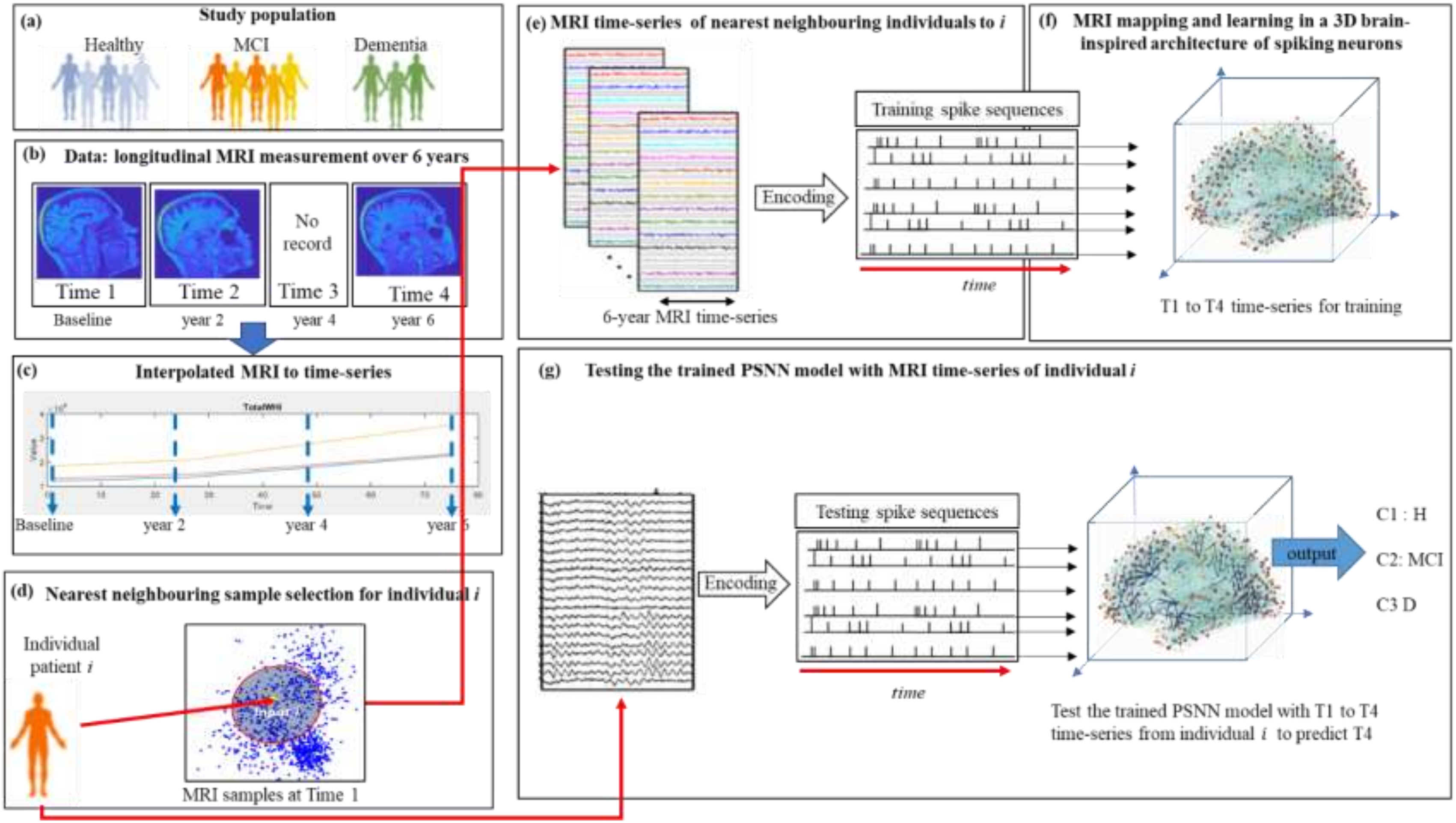
Doborjeh, M., and Kasabov, N., IEEE WCCI/IJCNN, 2016 (Response to treatment of drug addicts using clinical and EEG data)

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 modelling of **longitudinal MRI** data for the understanding and the prediction of progression to MCI and to AD (based on Sydney MAS data, P.Sadchev et al)

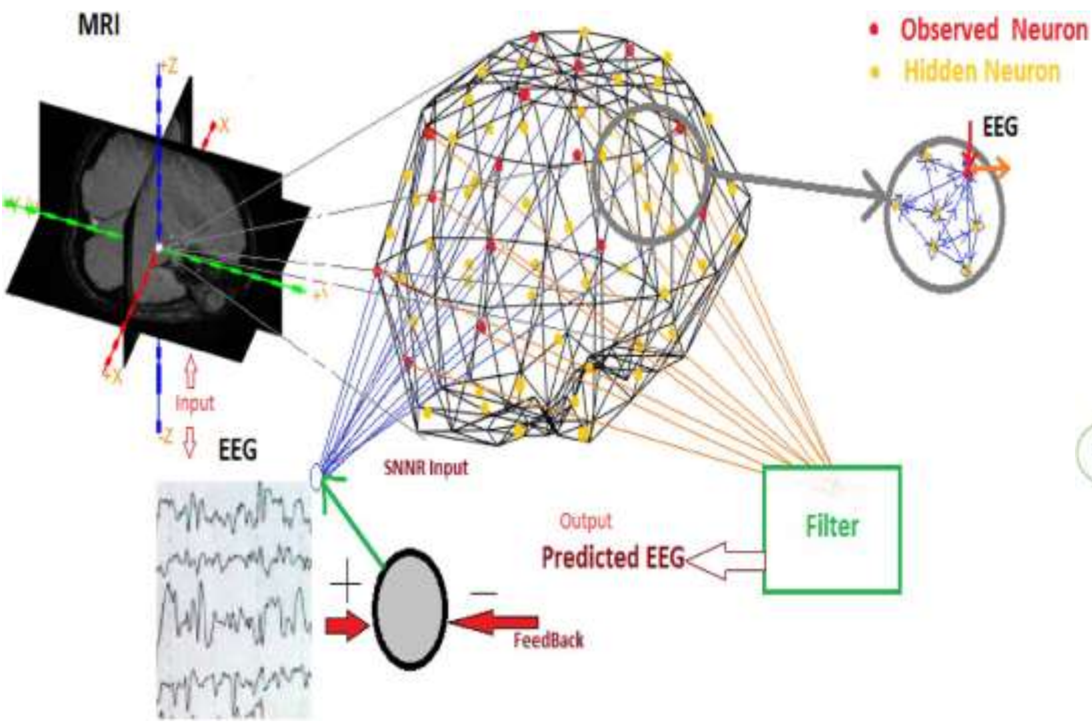


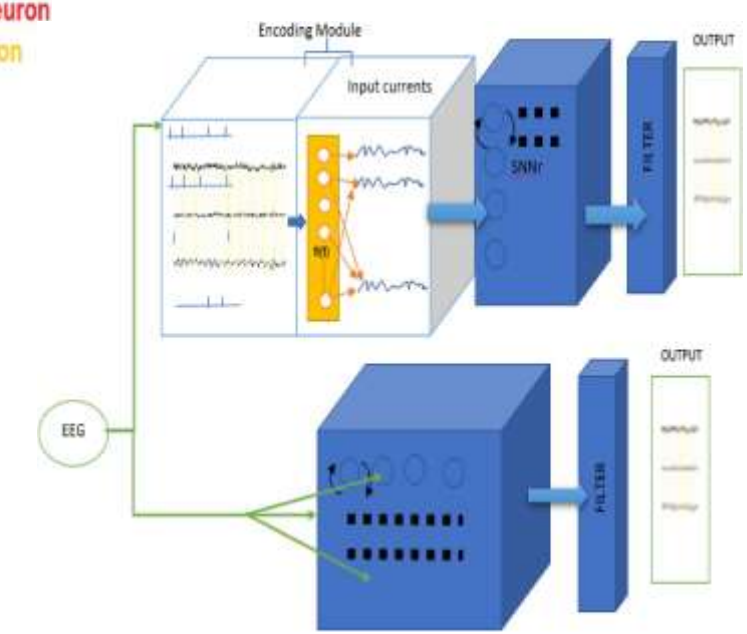
M. Doborjeh, Z.Doborjeh, A.Merkin, H.Bahrami, A.Sumich, R.Krishnamurthi, O. Medvedev, M.Crook-Rumsey, C. Morgan, I.Kirk, P.Sachdev, H. Brodaty, K. Kang, W.Wen, V. Feigin, N. Kasabov, Personalised Predictive Modelling with Spiking Neural Networks of Longitudinal MRI Neuroimaging Cohort and the Case Study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

MRI-> personal 3D brain template -> BI-SNN model

*S Saeedinia, MJahed-Motlagh, ATafakhori & N Kasabov, Personalised MRI structured BI-SNN and learning algorithms for personalized modelling, analysis, and prediction of EEG signals, Scientific Reports, **11**,12064 (2021)*

- Predictive modelling of EEG signals for predicting episodes of epilepsy





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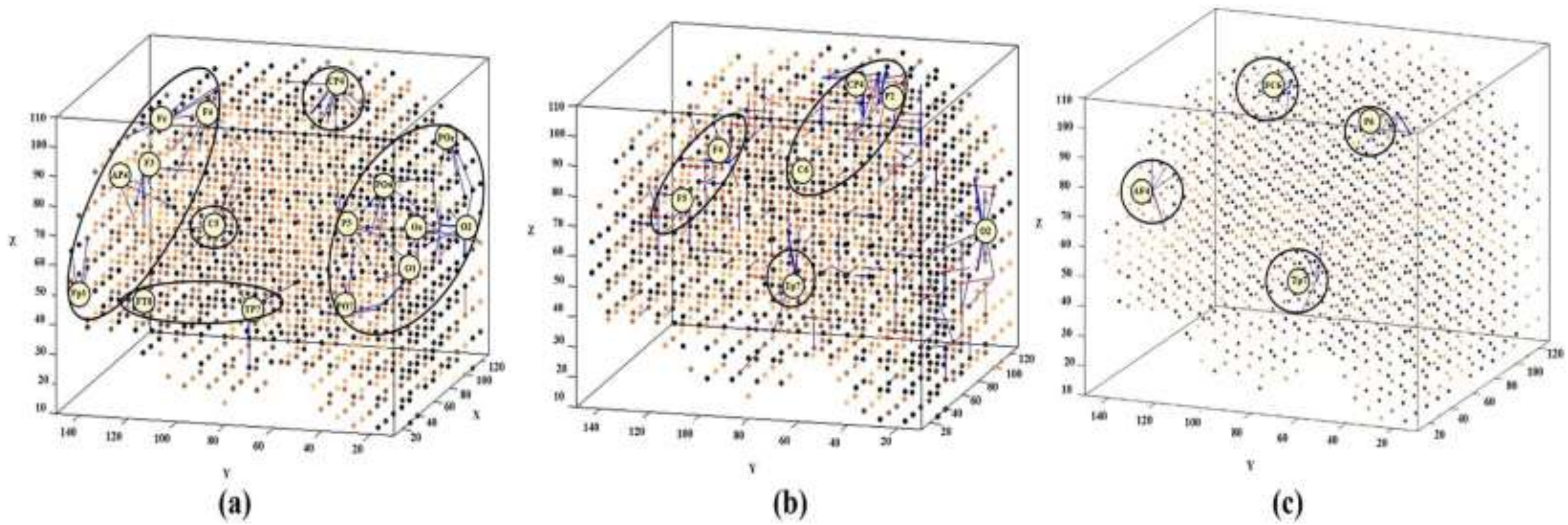
Intelligent Systems Research Centre

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)

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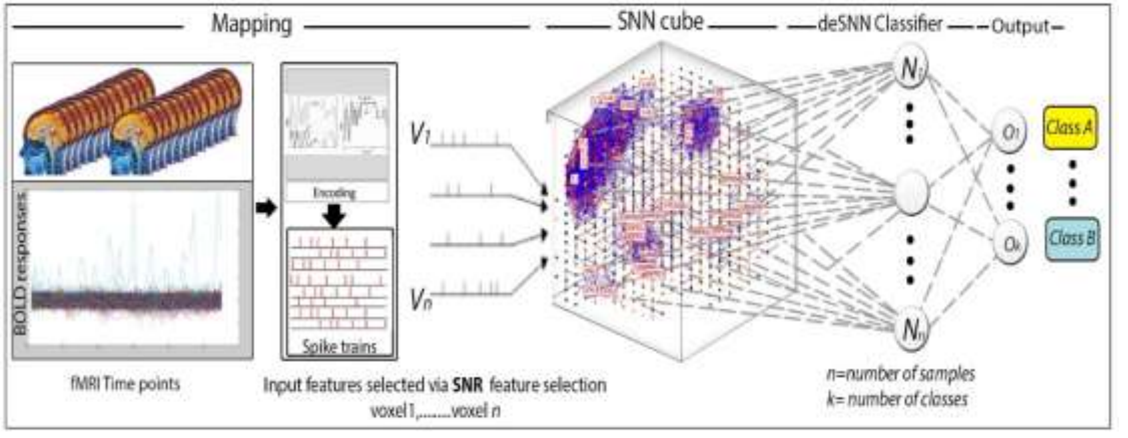
Deep learning and deep knowledge representation of personal fMRI data

Spatial mapping of fMRI voxels into a 3D SNN cube.

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

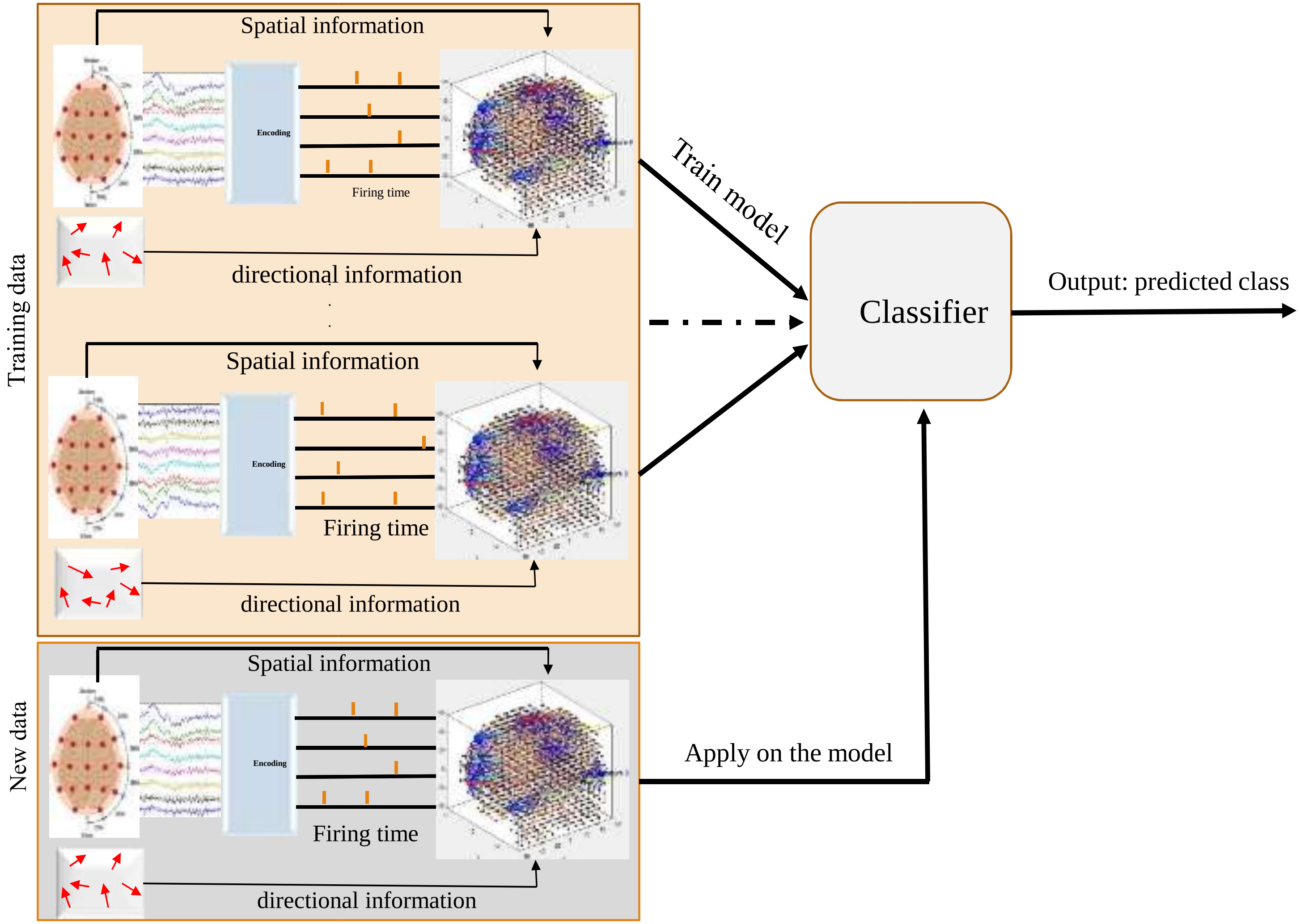


Method / Subject From STAR+ data (picture vs sentence perception)	SVM	MLP	NEUCUBE[B]
04799	50(20,80)	35(30,40)	90(100,80)
04820	40(30,50)	75(80,70)	90(80,100)
04847	45(60,30)	65(70,60)	90(100,80)
05675	60(40,80)	30(20,40)	80(100,60)
05680	40(70,10)	50(40,60)	90(80,100)
05710	55(60,50)	50(50,50)	90(100,80)

PM using both fMRI and DTI data

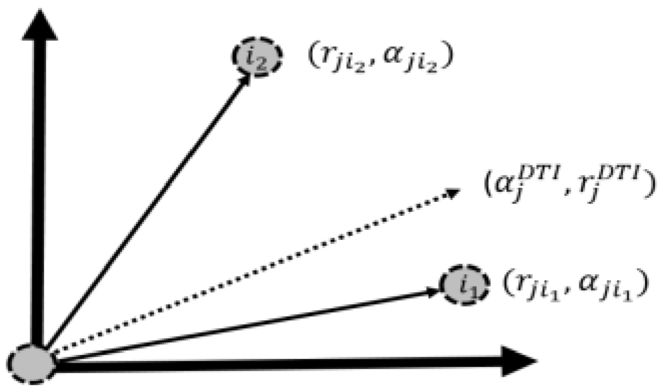
Case on response of schizophrenic patients to clozapine

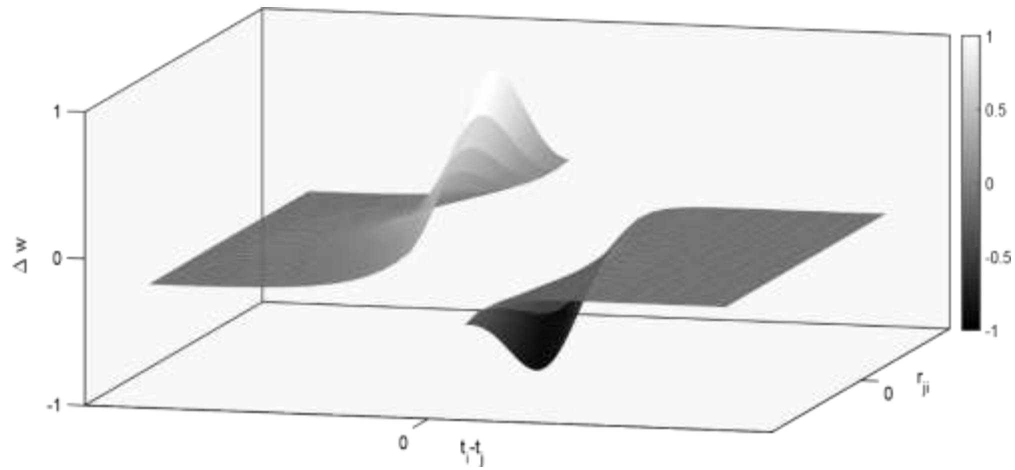
Sengupta, N., McNabb, C. B., Kasabov, N., & Russell, B. R. (2018). Integrating Space, Time, and Orientation in Spiking Neural Networks: A Case Study on Multimodal Brain Data Modelling. IEEE Transactions on Neural Networks and Learning Systems, 29(11). doi:10.1109/TNNLS.2018.2796023



Integrating Space, Time and Direction in NeuCube: A Case Study on fMRI + DTI brain data

A new learning rule is introduced: Orientation influenced STDP - oiSTDP





Method	Data	Temporal	Multi-dimensional	Accuracy(%)	Cohen's κ
BSA+oiSTDP+KNN	fMRI+DTI	yes	Yes	**72.3±12.3**	0.44±0.25
BSA+STDP+KNN	fMRI	Yes	no	69.4±13.9	0.38±0.28
BSA+KNN	fMRI	no	No	64.2±12.4	0.22±0.26
Sparse Autoencoder [45]+KNN(E) [44]	fMRI	No	no	56.1±7.2	0.01±0.11
PCA [44]+KNN(E) [44]	fMRI	no	No	56.1±11.3	0.13±0.18
ICA [44]+KNN(E) [44]	fMRI	no	No	62.8±12.3	0.26±0.23
RBM [44]+KNN(E) [44]	fMRI	no	no	36.2±4.9	−0.23±0.11
LSTM [45]	fMRI	yes	no	45.7±9.6	−0.15±0.14
GRU [45]	fMRI	yes	no	45.2±7.5	−0.018±0.13

N.Sengupta, C.McNabb, N.Kasabov, B.Russel, Integrating Space, Time and Orientation in Spiking Neural Networks: A Case Study on Multimodal Brain Data Modelling, IEEE Tr NNLS, 2017.

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).

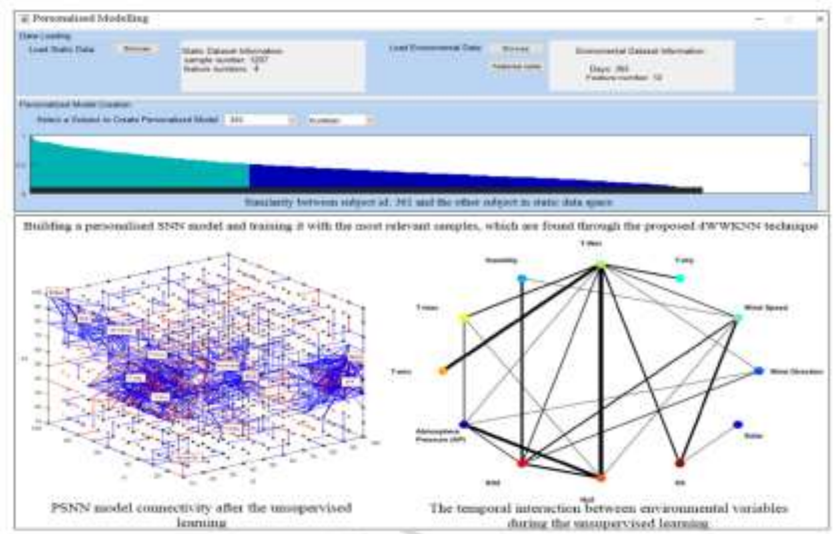


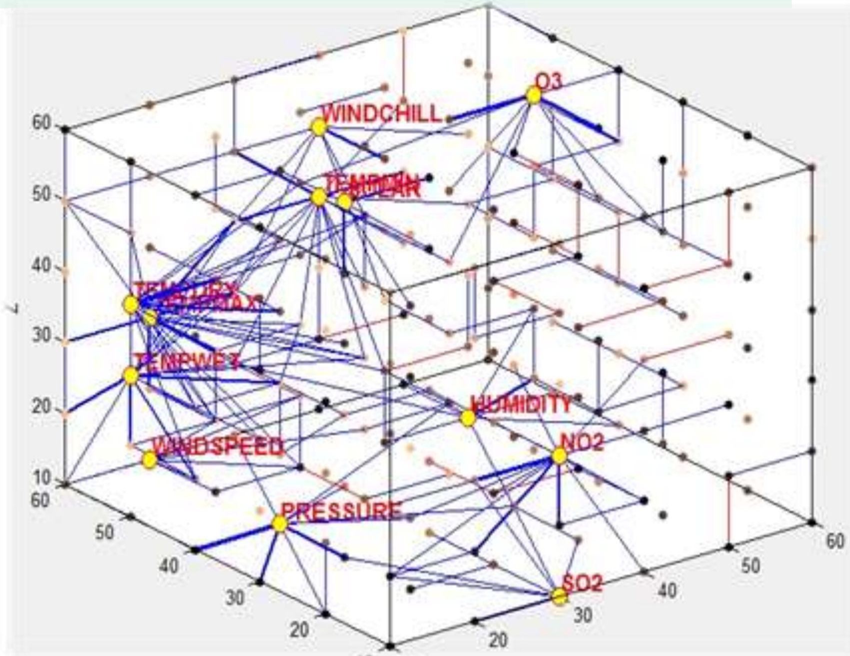
Fig. 9. The user interface of the proposed personalised predictive system for prediction of risk of stroke. A PSNN model is created to spatially map the environmental variables, where the most correlated variables are mapped to closer input neurons. Then the PSNN model was trained on the temporal spike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

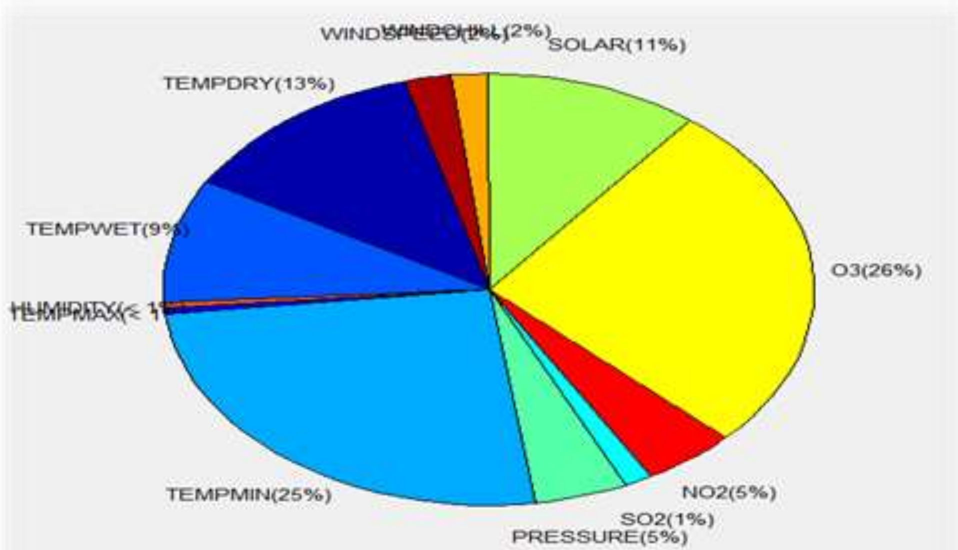
Maryam Doborjeh, Zohreh Doborjeh, Alexander Merkin, Rita Krishnamurthi, Reza Enayatollahi, Valery Feigin, **Nikola Kasabov**, Personalised Spiking Neural Network Models of Clinical and Environmental Factors to Predict Stroke, Cognitive Computation, COGN-D-20-00511R2, 26 , 2021, https://www.springer.com/journal/12559.

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

Using ECOS and BI-SNN for PM results in a better predictive accuracy and good explainability

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

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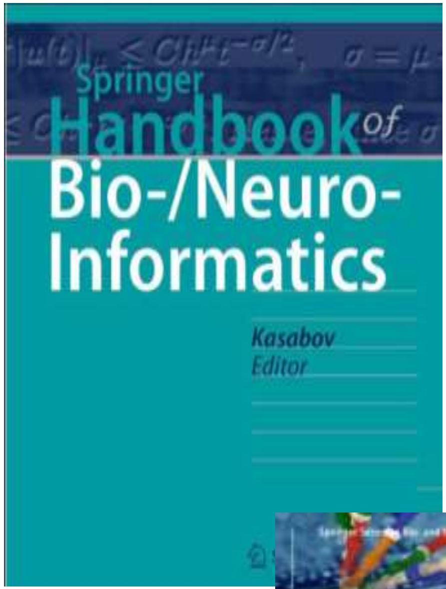
6. Discussions and future directions

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

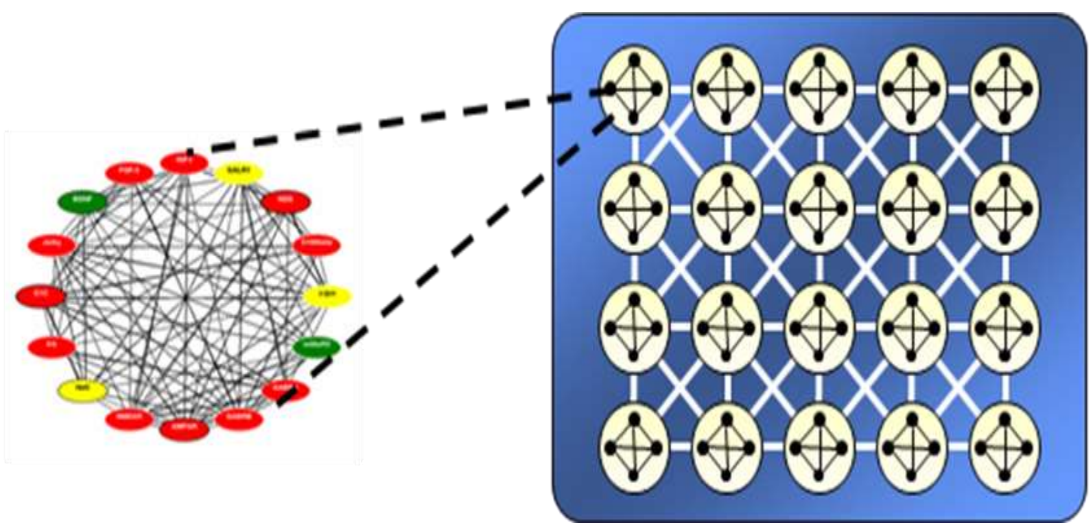
- Sensitive to parameter values
- Large number of parameters to be optimised
- No rigid theory yet.
- Ethical issues: www.mindthegap.ai

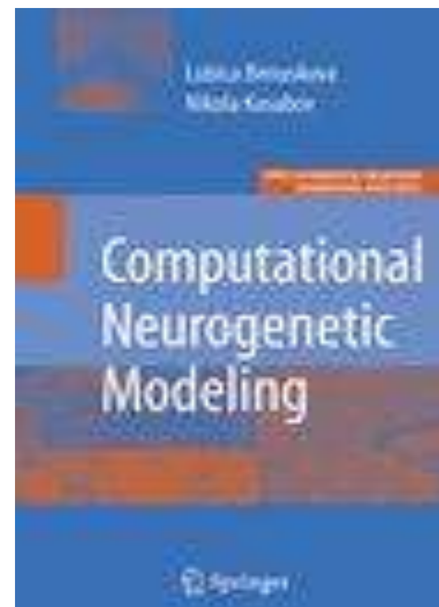
Computational Neuro-Genetic Modelling (CNGM)

- Benuskova and Kasabov (Springer, 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.

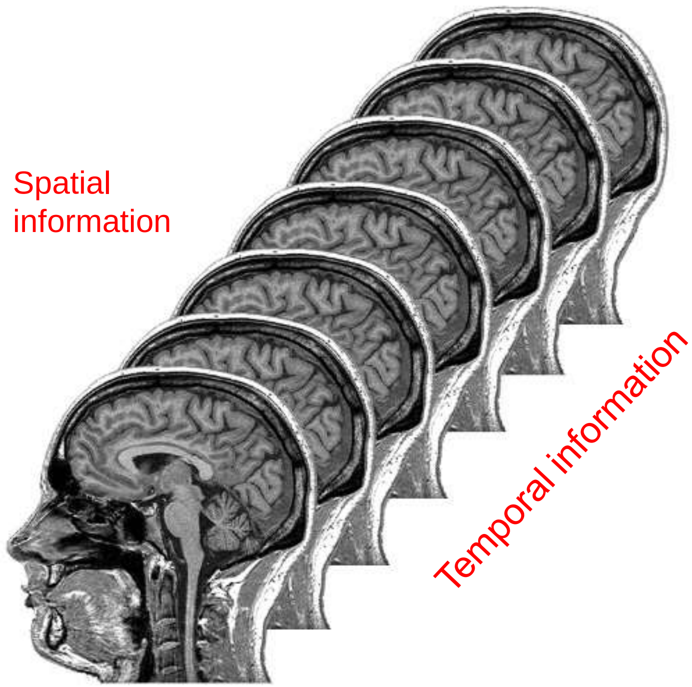
- Functions of neurons and neural networks are influenced by internal networks of interacting genes and proteins forming an abstract GRN model.
- The GRN and the SNN function at different time scales.

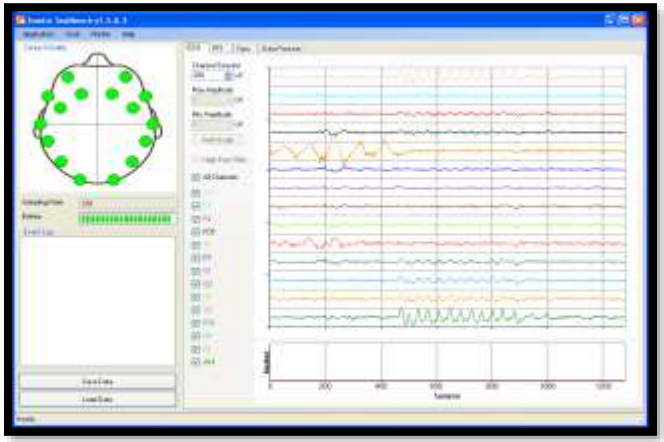




Integrating multimodal neuroimaging data

Spatial
information

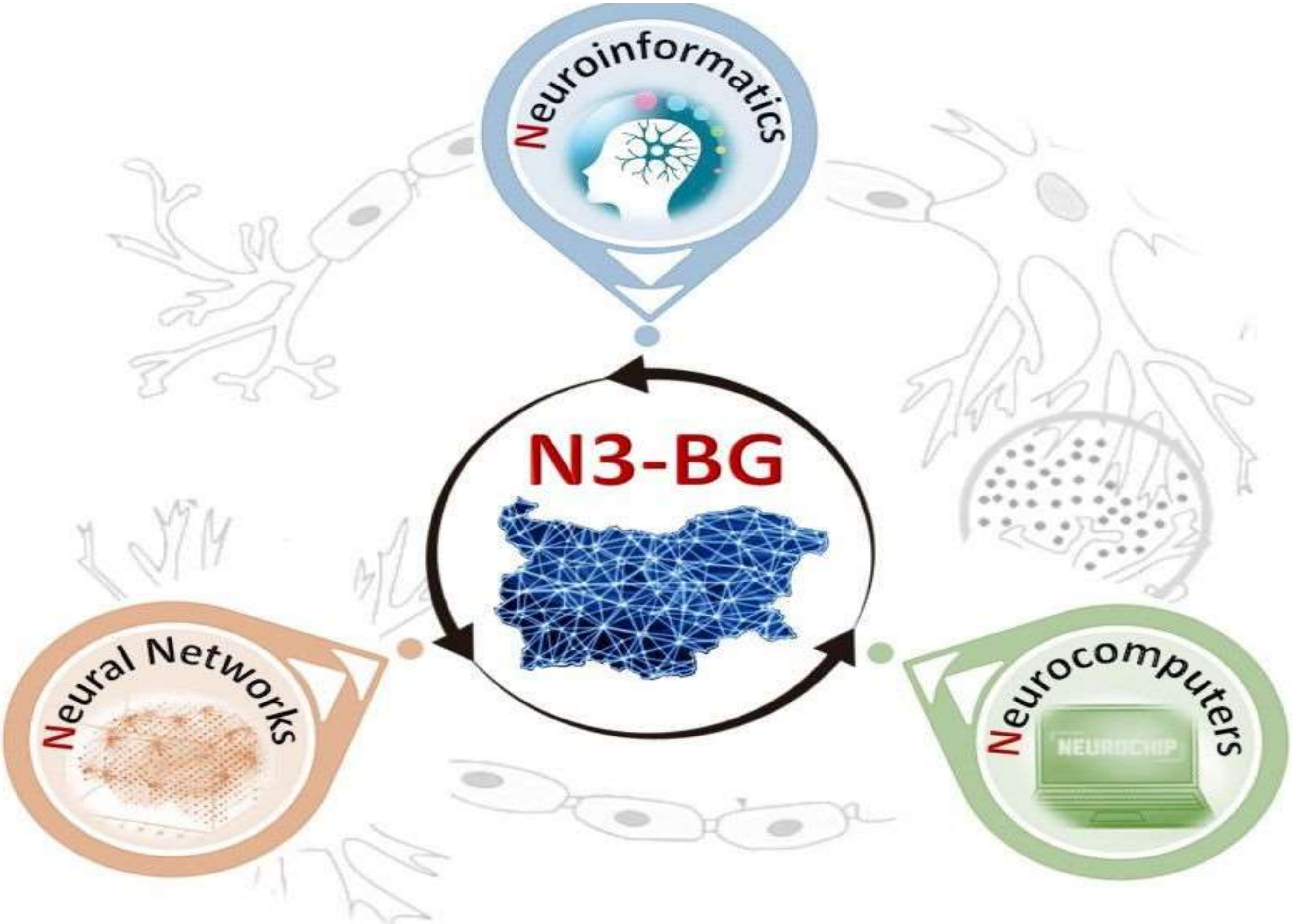




Modelling simultaneously EEG and fMRI data is an open problem:
- different time scales
- different spatial resolution

The **N3-BG** group (Neuroinformatics, Neural networks and Neurocomputers)

https://www.knowledgeengineering.ai/n3-bg



Thank you!

For contacts: N.Kasabov (nkasabov@aut.ac.nz) or Ms Iman AbouHassan (iabouhassan@tu-sofia.bg)