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Neuro-inspired computation: Spiking Neural Networks

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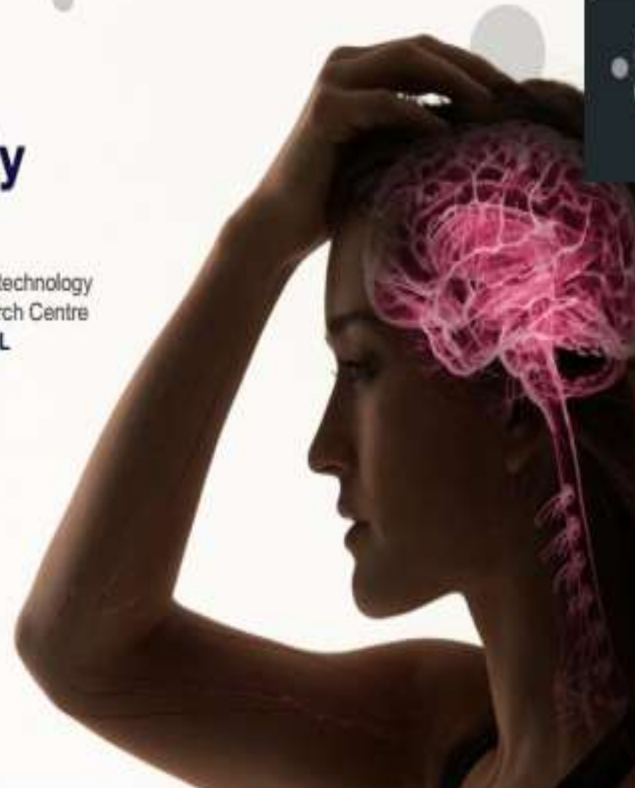
Research themes

- Cognitive Robotics
- Computational Neuroscience & Neuromorphic Engineering
- Cognitive Neuroscience & Neurotechnology
- Intelligent Data Analytics
- Spatial Computing & Future Human-Computer Interaction
- Cyber Security & Web Technologies



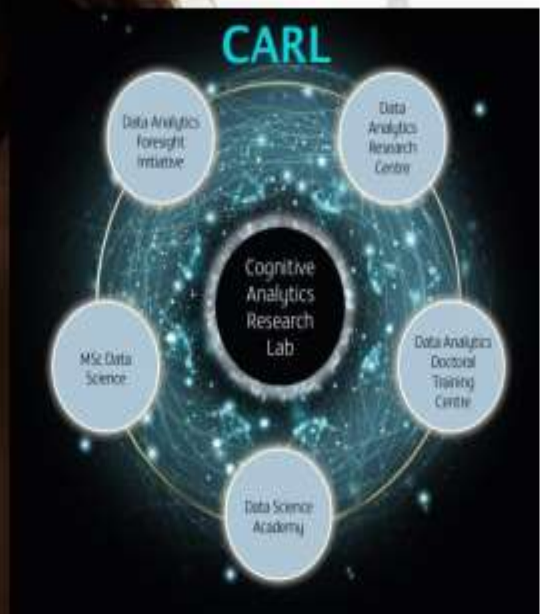
Our facilities

NIFBM — Northern Ireland Functional Brain Mapping Facility houses the only magnetoencephalography (MEG) system in Ireland (1 of 10 in the UK).

SCAN iHub — Spatial Computing & Neurotechnology Innovation Hub – next generation human computer interaction

Brain-Computer Interface lab

Advanced cognitive robotics lab



Vision

Our vision is to develop a bio-inspired computational basis for Artificial Intelligence to power future cognitive technologies.

Mission

Our mission is to understand how the brain works at multiple levels, from cells to cognition and apply that understanding to create realistic models and construct technologies that solve the complex issues that face people and society. To accomplish our mission we use a variety of research strategies that include big data and machine learning, brain imaging and neural interfacing, human-computer interaction and robotics.

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Synopses

The lecture introduces the third generation of artificial neural networks, the spiking neural networks (SNN), as the latest methods and systems for neuro-inspired computation, along with their numerous applications. SNN are not only capable of deep learning of temporal or spatio-temporal data, but also enabling the extraction of knowledge representation from the learned data. Similarly to how the brain learns, these SNN models do not need to be restricted in number of layers, neurons in each layer, etc. as they adopt self-organising learning principles of the brain.

The lecture consists of 3 parts:

- Fundamentals of SNN
- Brain-inspired SNN architectures. NeuCube.
- Design and implementation of selected applications

The material is illustrated on an exemplar SNN architecture NeuCube (free software and open source available from www.kedri.aut.ac.nz/neucube). Case studies are presented of brain and environmental data modelling and knowledge representation using incremental and transfer learning algorithms. These include: predictive modelling of EEG and fMRI data measuring cognitive processes and response to treatment; prediction dementia and AD [3]; understanding depression; predicting environmental hazards and extreme events; moving object recognition and control; brain-inspired audio-visual information processing.

It is also demonstrated that SNN allow for knowledge transfer between humans and machines through building brain-inspired Brain-Computer Interfaces (BI-BCI) [4]. These are used to understand human-to-human knowledge transfer through hyper-scanning and also to create brain-like neuro-rehabilitation robots. This opens the way to build a new type of AI systems – the open and transparent AI.

References:

N. K. Kasabov, "NeuCube: A spiking neural network architecture for mapping, learning and understanding of spatio-temporal brain data," Neural Networks, vol. 52, pp. 62-76, 2014.

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

M. Doborjeh, …, 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 (available from https://authors.elsevier.com/c/1dsCu3BBjKgGro

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

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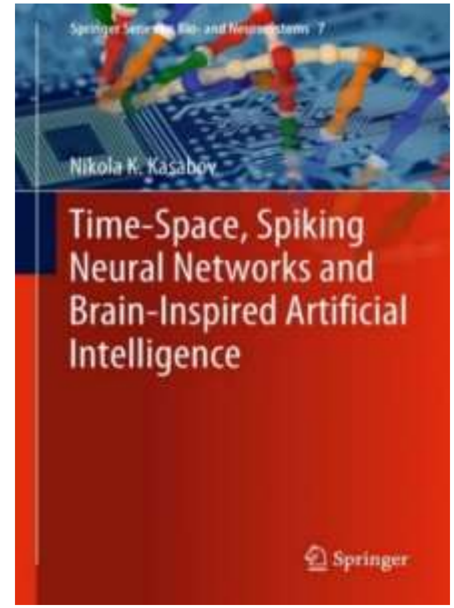
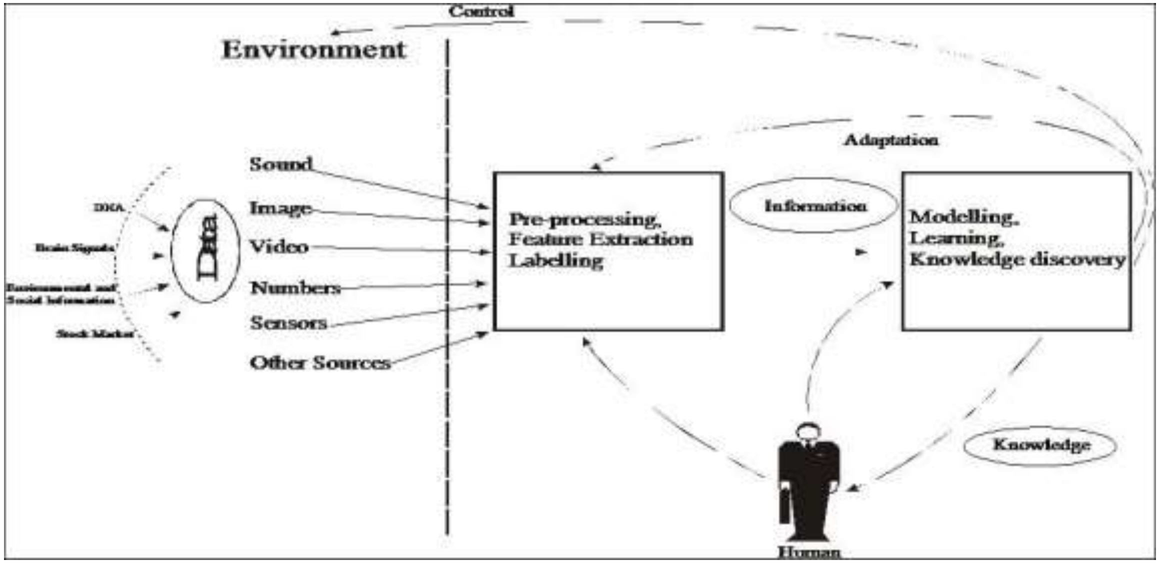
Content

1. Why neuro-inspired computation? Inspiration from the brain
2. Fundamentals of SNN
3. Brain-inspired SNN. NeuCube
4. Design and implementation of SNN systems
5. Applications
6. Conclusion and further directions



N.Kasabov, Time-space, spiking neural networks and brain-inspired artificial intelligence, Springer, 2019. https://www.springer.com/gp/book/9783662577134

1. Why neuro-inspired computation. Inspiration from the brain



Looking for new methods to deal with multimodal data: from data-, to information and knowledge

Searching: Observe phenomena; Collect Data; Store data;

- **A**nalysis (e.g. pre-process data, filter, select features, visualise, label): Information
- **L**earning (create a model, validation and reasoning)
- **K**nowledge creation (Create/extract rules) and reasoning (deductive, inductive)
- **A**daptation (accommodate new data and knowledge)

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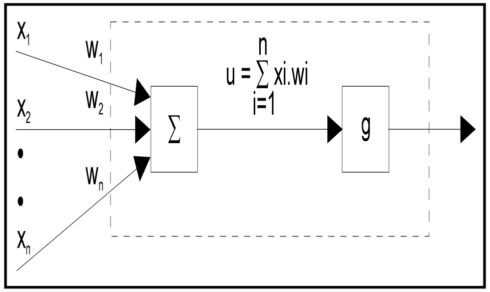
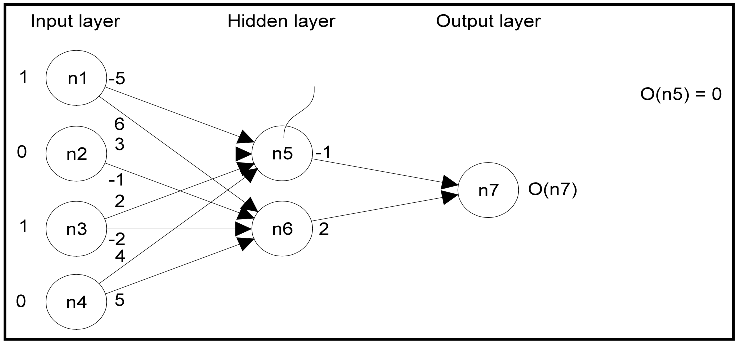
Artificial Neural Networks

- 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, Rosenblatt - Perceptron
- 1971- 1986, Amari, Rumelhart, Werbos: Multilayer perceptron
- Many engineering applications.



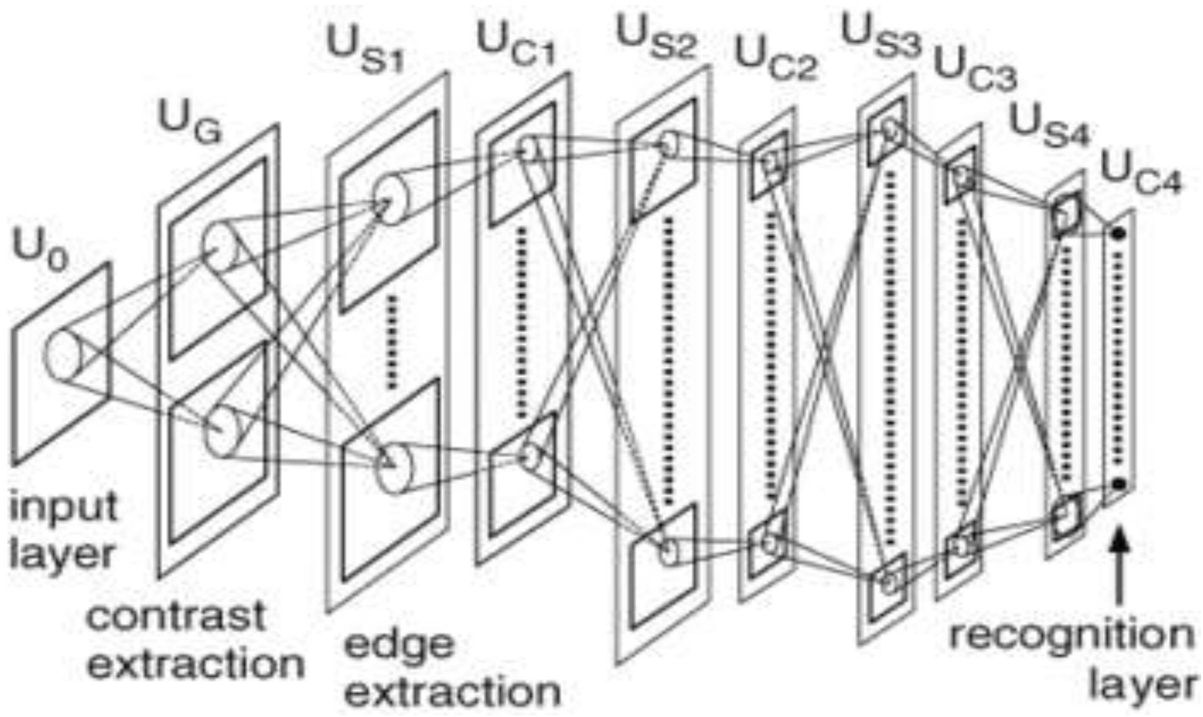
- Early NN were 'black boxes' and also - once trained, difficult to adapt to new data without much 'forgetting'.



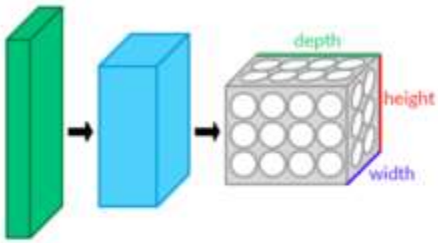
Early deep convolutional NN in computer vision

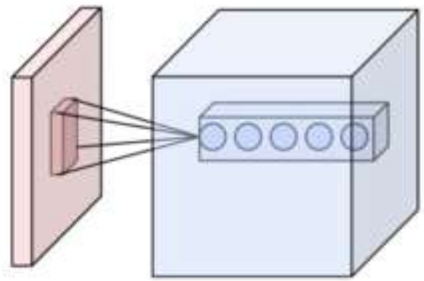
Spatial features are represented (learned) in different layers of neurons

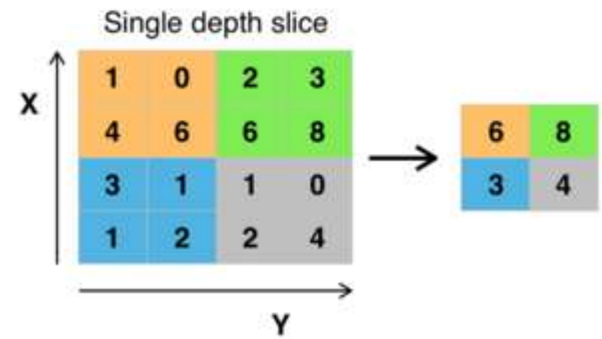
Fukushima's Cognitron (1975) and Neocognitron (1980) for image processing

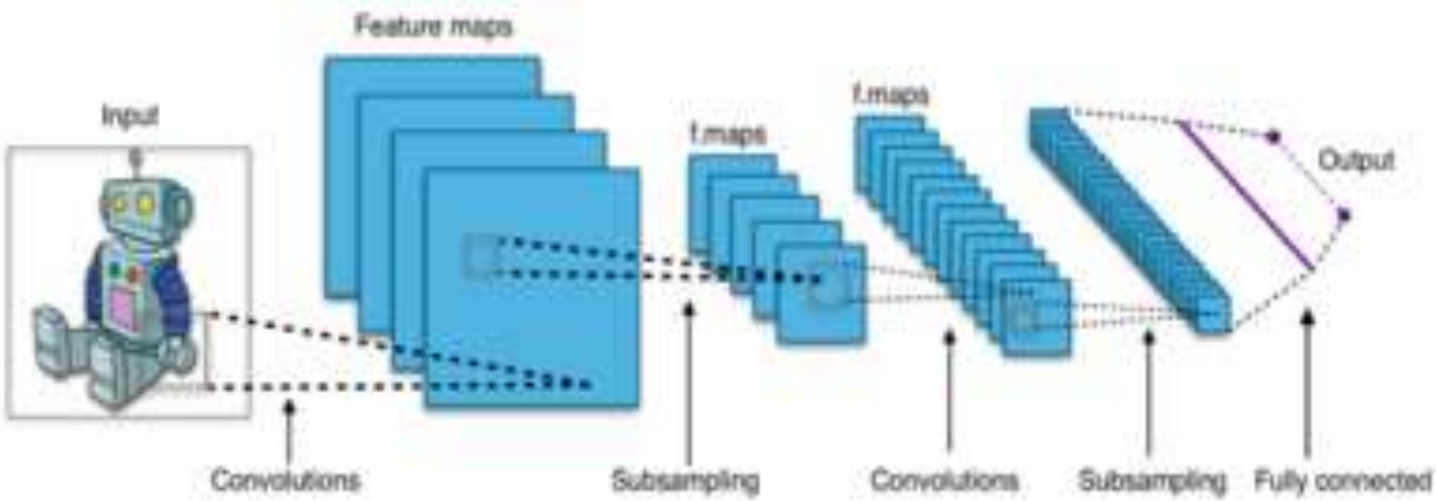


Deep Convolutional Neural Networks









Deep NN are excellent for vector, frame- based data (e.g. image recognition) but not for spatio-temporal or temporal data and for knowledge extraction.

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Inspiration from the brain

Deep learning and deep knowledge representation in the human brain

The human brain, the most sophisticated product of the evolution, is a deep learning machine

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.

Spatially evolved structure with spatially allocated functions

Knowledge is represented as deep spatio-temporal patterns

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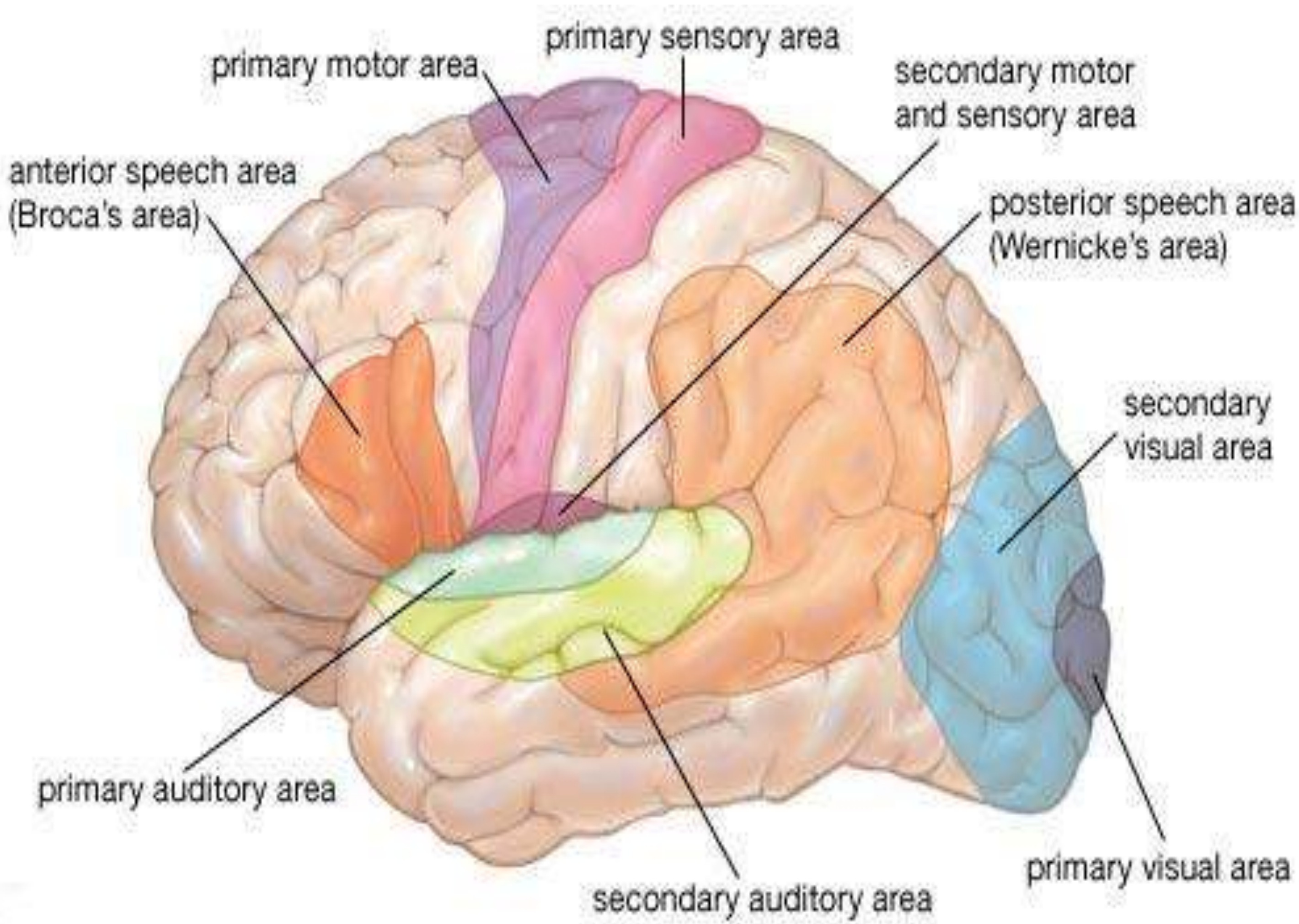
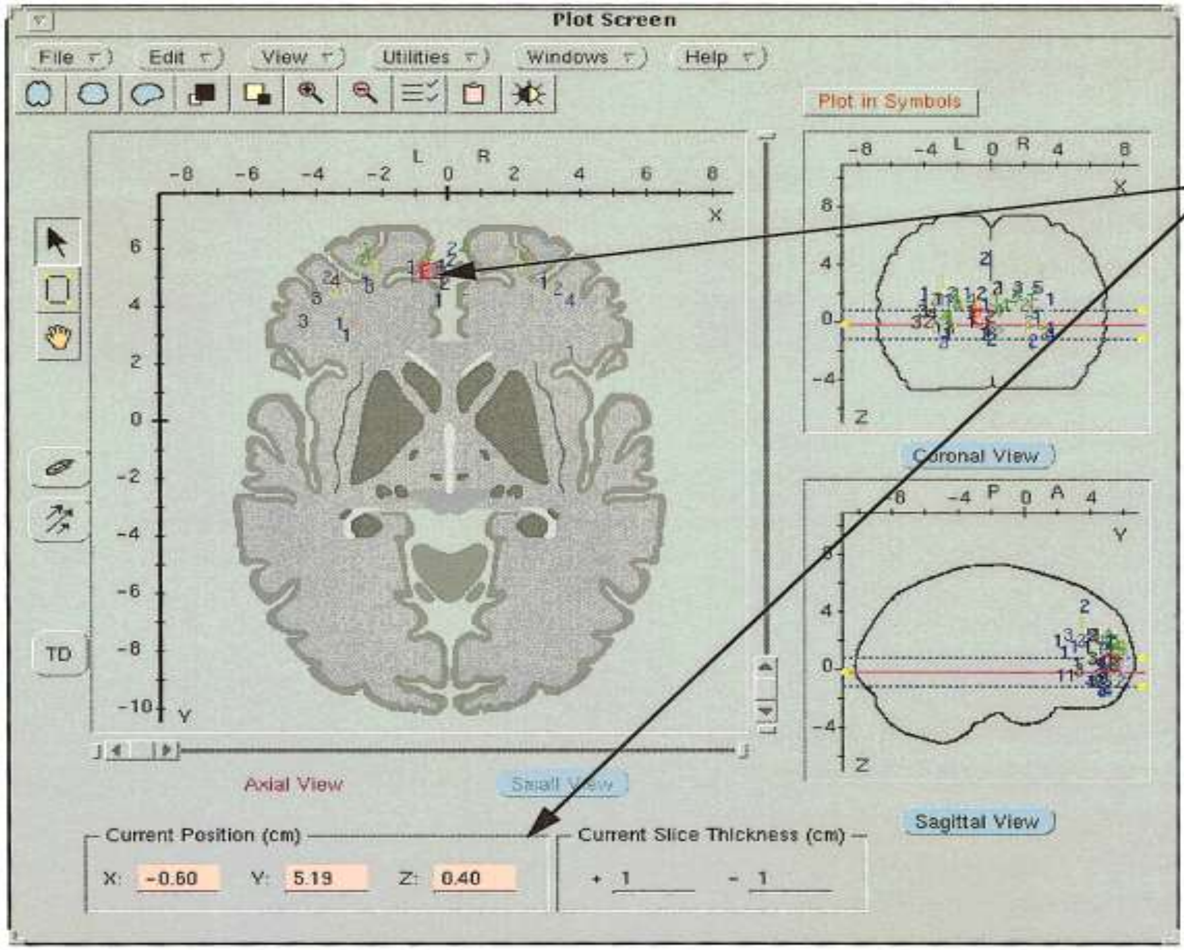
Different parts of the brain control different functions



Brain Atlases: Brain spatial information

Talairach Atlas – Talairach Daemon

http://www.talairach.org/daemon.html



Talairach Label

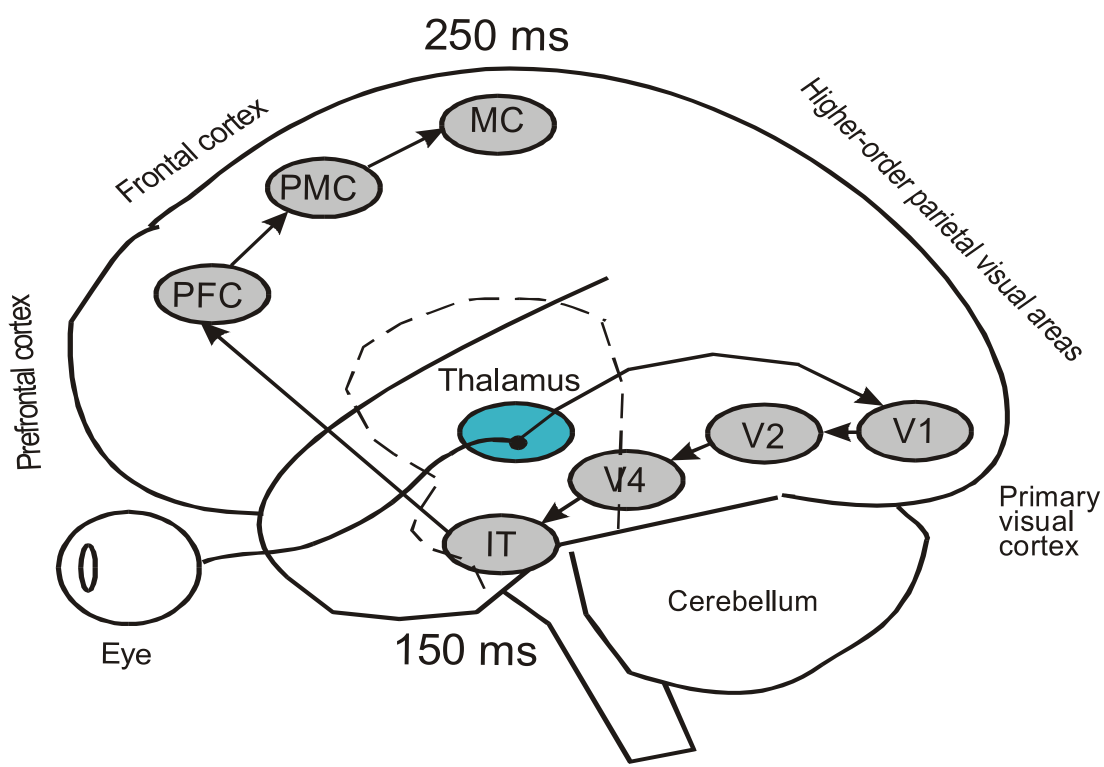
Left Cerebrum
Frontal Lobe
Medial Frontal Gyrus
Gray Matter
Brodmann area 10

x = -6 mm
y = 52 mm
z = 4 mm

Query on Brodmann Area 10 yielded:

- **32 papers**
- **46 experiments**

Learning in the brain is in time and space: Image recognition

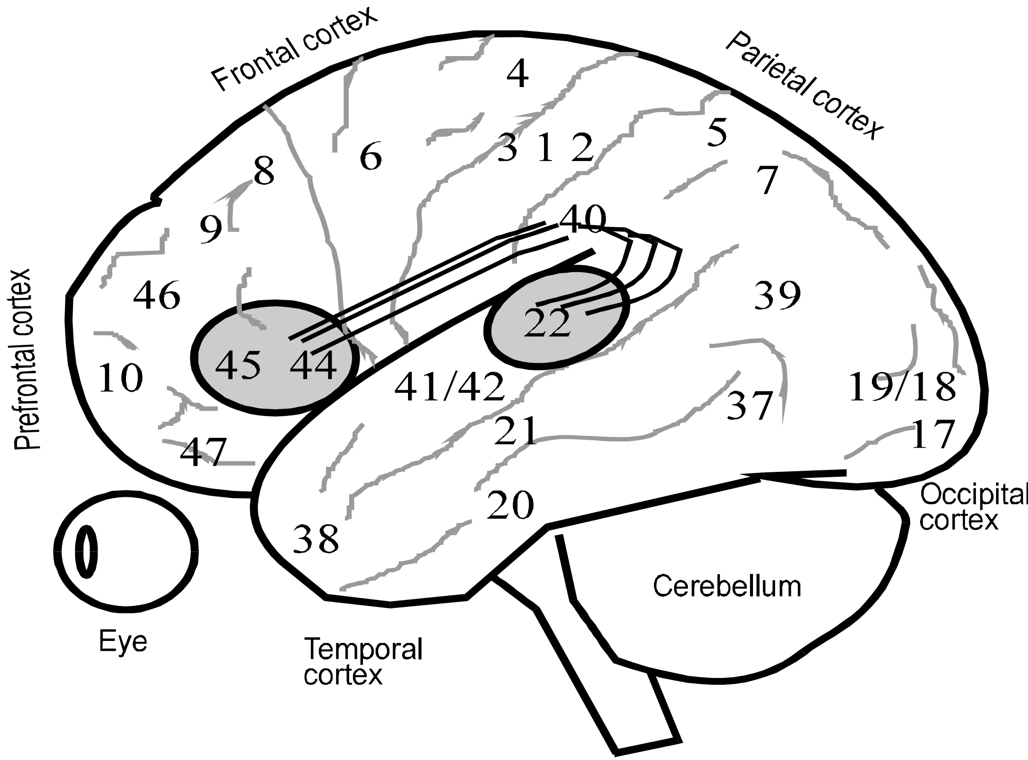


Deep serial processing of visual stimuli in humans for image classification and action.

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)

Language learning and processing

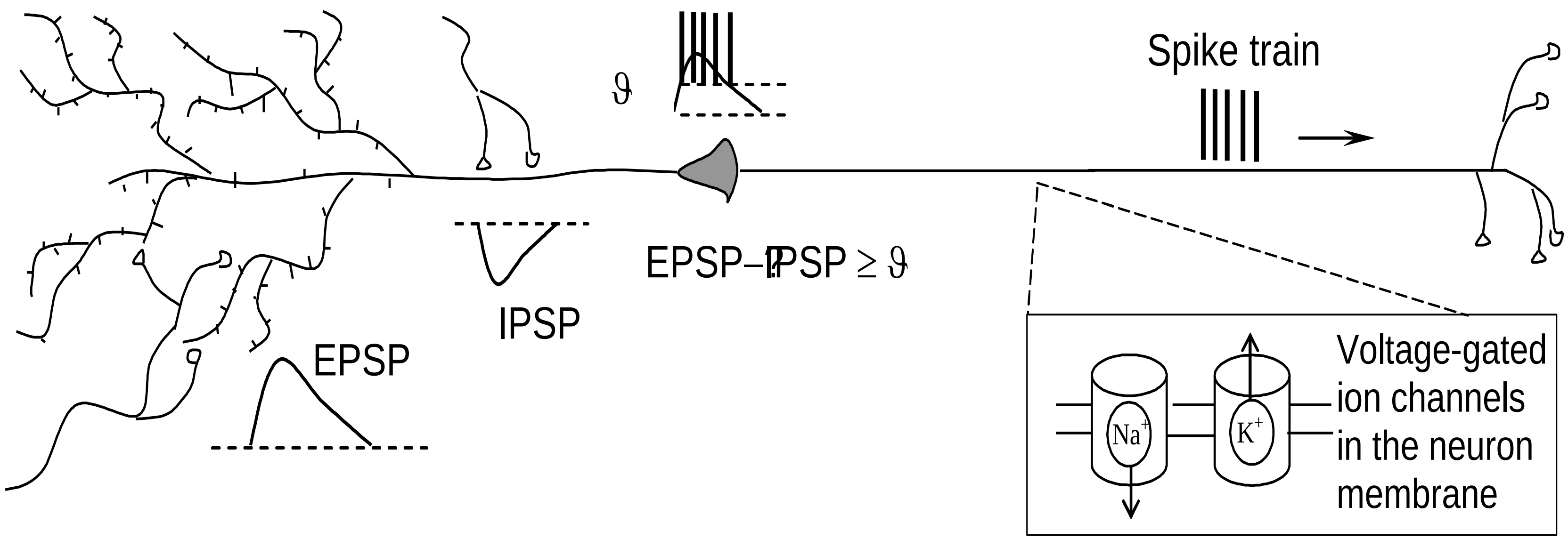


(from L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer, 2007)

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.

Spiking activities of neurons

Electric synaptic potentials and axonal ion channels responsible for spike generation and propagation: EPSP = excitatory postsynaptic potential, IPSP = inhibitory postsynaptic potential, ϑ = excitatory threshold for an output spike generation.



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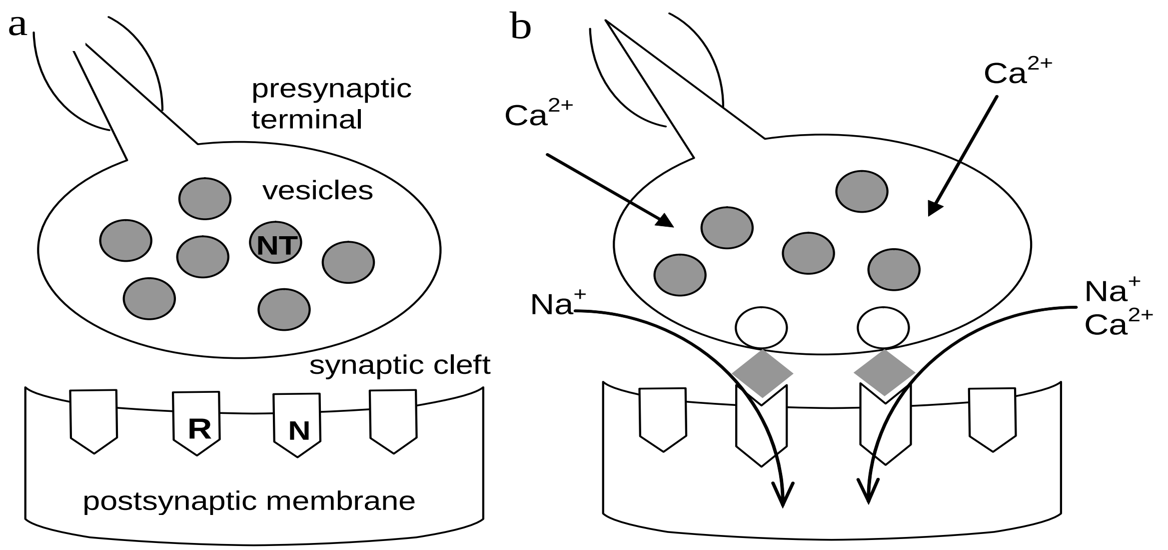
Gene-based chemical processes in the synapses define spiking activity in neurons



Abbreviation:

NT: neurotransmitter,

R : AMPA-receptor-gated ion channel for sodium,

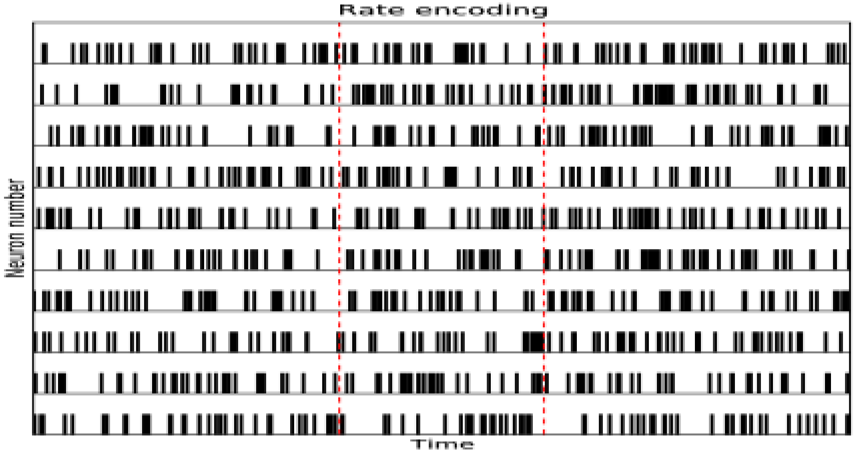
N: NMDA-receptor-gated ion channel for sodium and calcium.

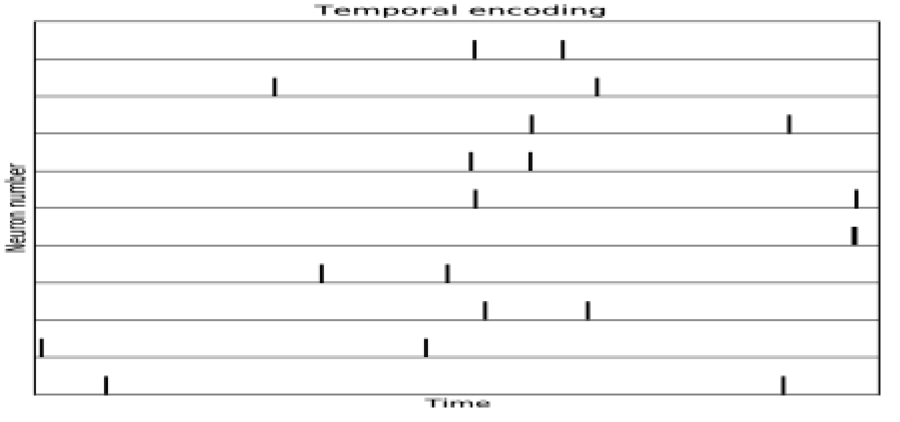
- Ion channels with quantum properties affect spiking activities in a stochastic way. "To spike or not to spike?" is a matter of *probability.*
- Transmission of electric signal in a chemical synapse upon arrival of action potential into the terminal is probabilistic
- Emission of a spike on the axon is also probabilistic
- Prior art on stochastic modelling of neuronal processes : D. Colguhoun, B. Sakmann, E. Neher, SShoman, SWang, DTank , JHopfield

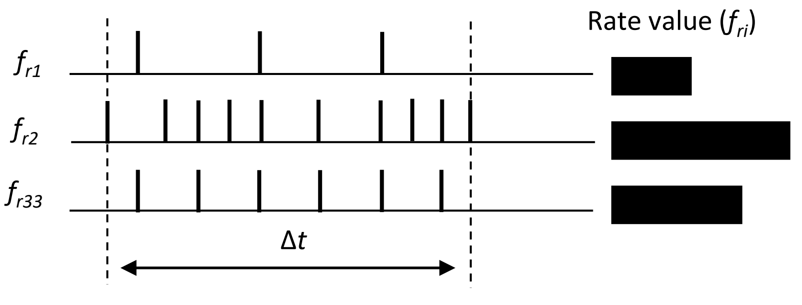
2. Fundamentals of Spiking Neural Networks

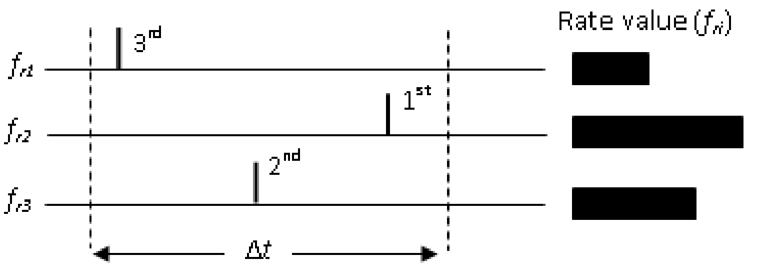
Spike encoding:

- Rate-based coding: A spiking characteristic within a time interval, e.g. frequency.
- Time-based (temporal) coding: Information is encoded in the time of spikes. Every spike matters and its time - too!







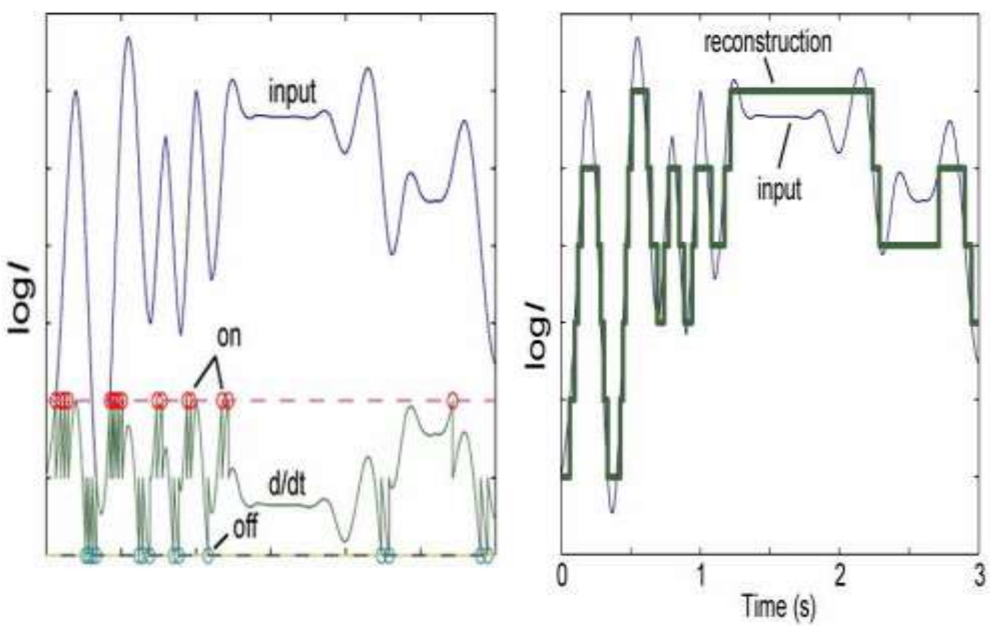


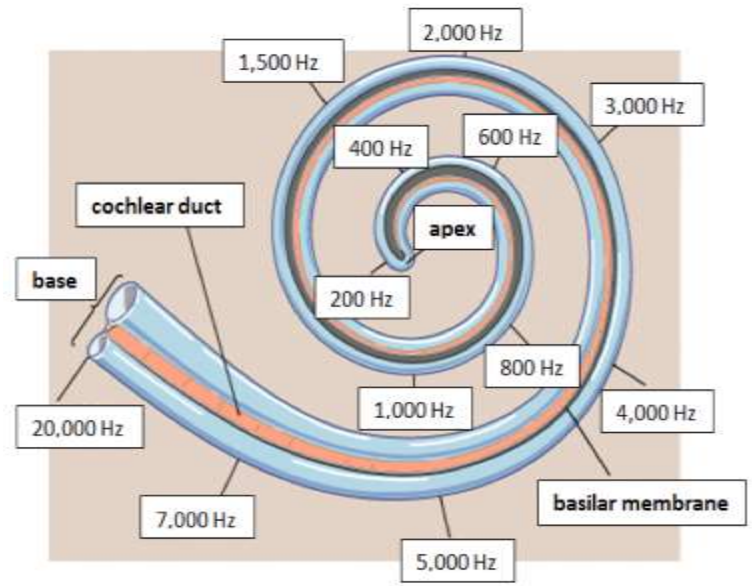
Spike encoding methods

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



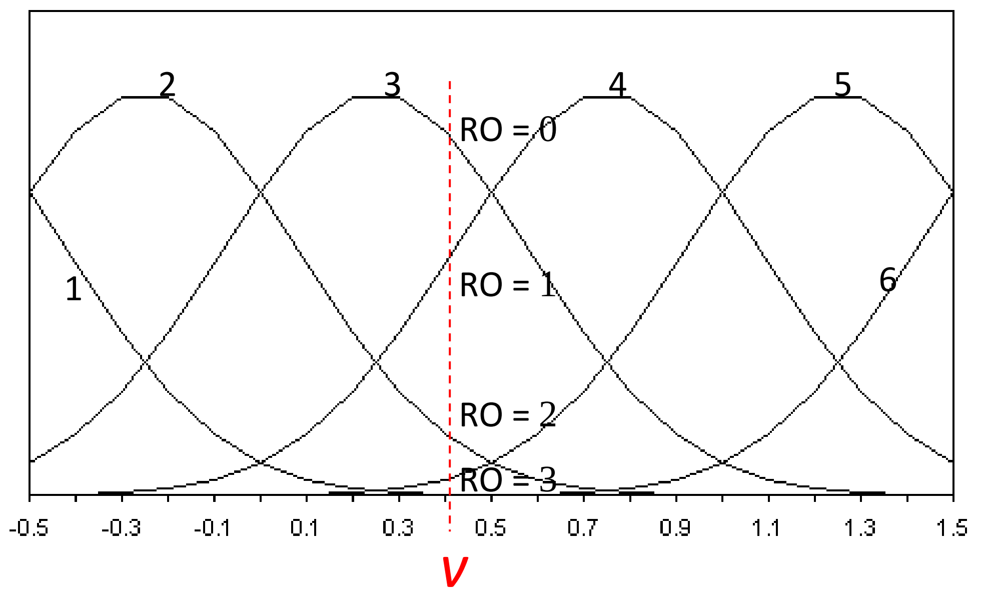


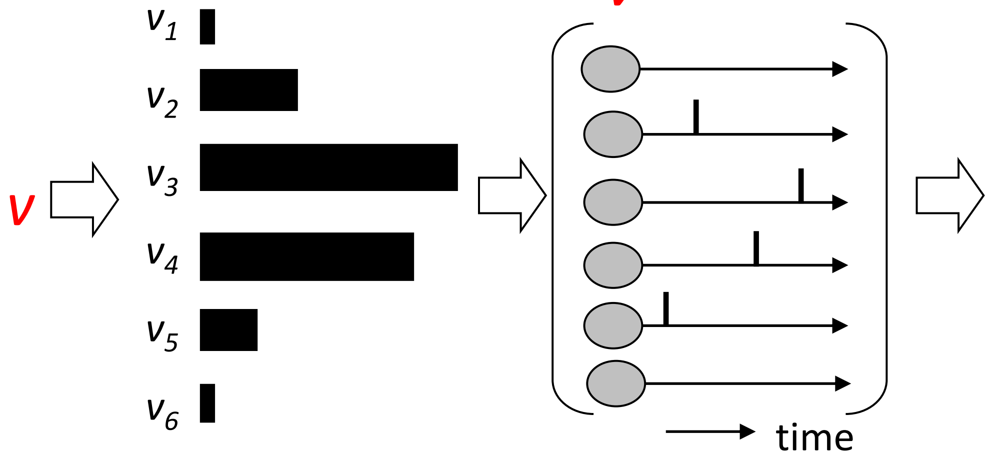
Threshold-based encoding – retinotopic

Tonotopic organization of the cochlea:
https://sites.google.com/site/jayanthinyswebite

RO population coding(RO-POP C)

Distributes a single real input value V to multiple neurons and may cause the excitation and firing of several responding neurons depending on the membership to the receptive fields.
Implementation based on Gaussian receptive fields introduced by Bothe *et al* . 2002





$O = \{-, 2, 0, 1, 3, -\}$

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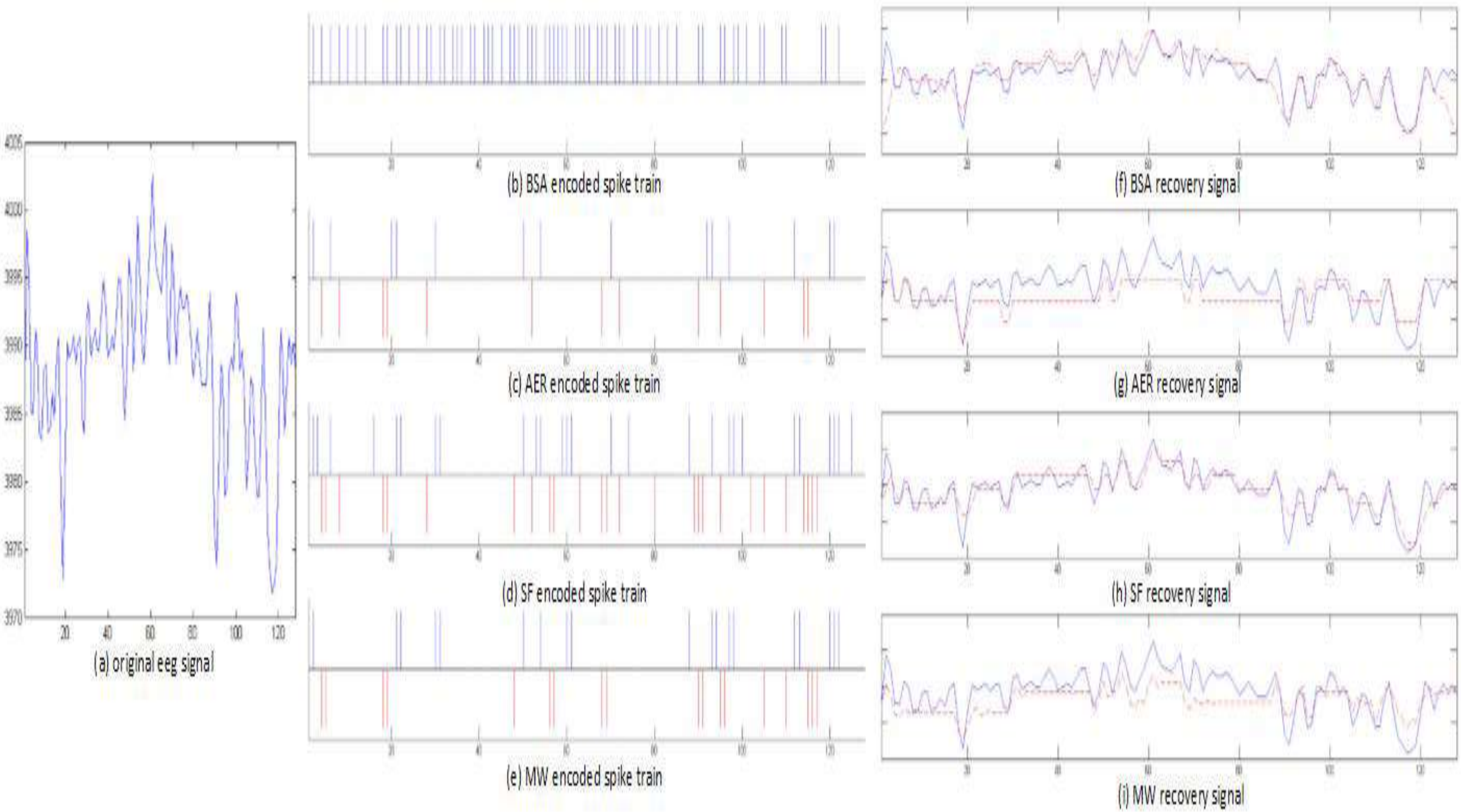
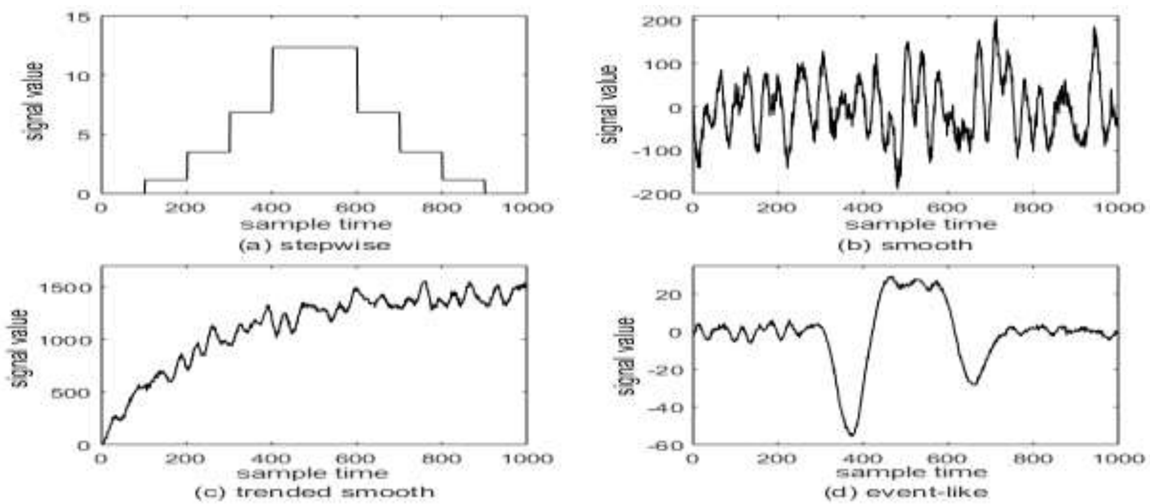
Input data encoding – which method to use?

(N. Kasabov, L. Zhou, M. Gholami Doborjeh, J. Yang, "New Algorithms for Encoding, Learning and Classification of fMRI Data in a Spiking Neural Network Architecture: A Case on Modelling and Understanding of Dynamic Cognitive Processes", IEEE Transaction on Cognitive and Developmental Systems, 2017, DOI: 10.1109/TCDS.2016.2636291.
)



Selection and optimisation of spike encoding method

((B.Petro, N.Kasabov, R.Kiss, Selection and optimisation of spike encoding methods for spiking neural networks, algorithms, IEEE Transactions of Neural Networks and Learning Systems, April 2019, DOI:10.1109/TNNLS.2019.2906158))



Four encoding methods are analyzed: one stimulus estimation [Ben's Spiker algorithm (BSA)] and three temporal contrast [threshold -based, step-forward (SF), and moving-window (MW)] encodings.

BSA can follow smoothly changing signals if filter coefficients are scaled appropriately.

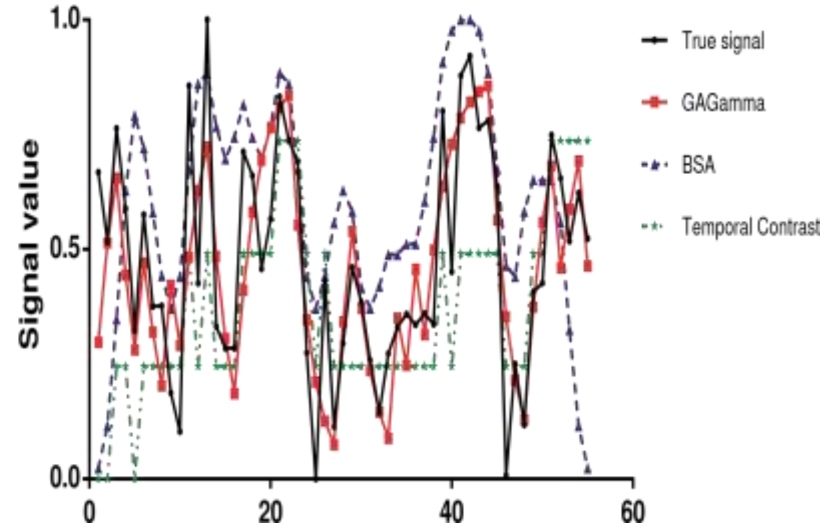
SF encoding was most effective for all types of signals as it proved to be robust and easy to optimize.

Signal-to-noise ratio (SNR) can be recommended as the error metric for parameter optimization.

Free software: https://github.com/KEDRI-AUT/snn-encoder-tools (Balint Petro, BU Hungary)

Spike encoding as data compression and noise suppression

subject id	Method	data type	bits/symbol	decoding error	Accuracy(K-NN)
04847	GAGamma	Integer	4.96	0.07	87.41 ± 4.80%(16)
	BSA	Integer	1.33	0.15	84.50 ± 4.47%(3)
	Temporal Contrast	Integer	1.95	0.23	54.16 ± 5.77%(1)
	Random	Integer	3.63	–	52.58 ± 4.79%(1)
	No encoding	Float	32.0	–	89.55 ± 4.60%(1)
07510	GAGamma	Integer	4.97	0.06	76.00 ± 5.89(8)
	BSA	Integer	1.28	0.15	74.08 ± 6.71%(8)
	Temporal Contrast	Integer	1.82	0.26	52.75 ± 5.84%(2)
	Random	Integer	3.63	–	52.58 ± 4.79%(1)
	No encoding	Float	32.0	–	79.11 ± 3.99%(5)

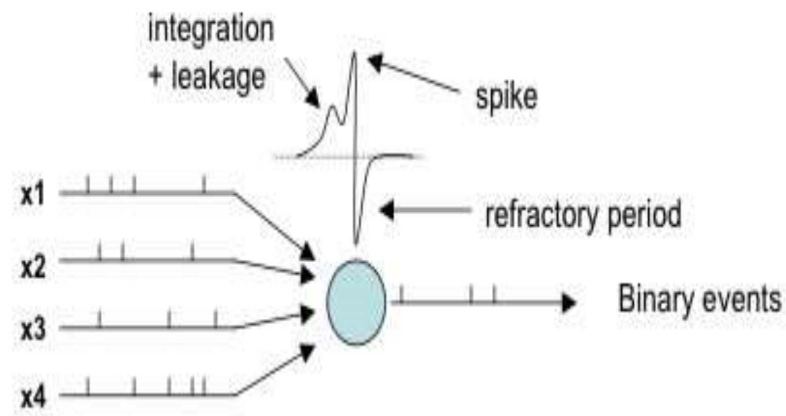


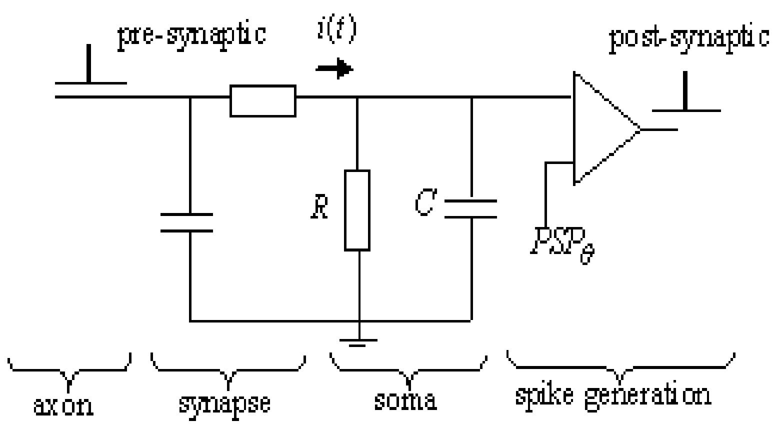
N.Sengupta, N. Kasabov, Spike-time encoding as a data compression technique for pattern recognition of temporal data, Information Sciences 406–407 (2017) 133–145.

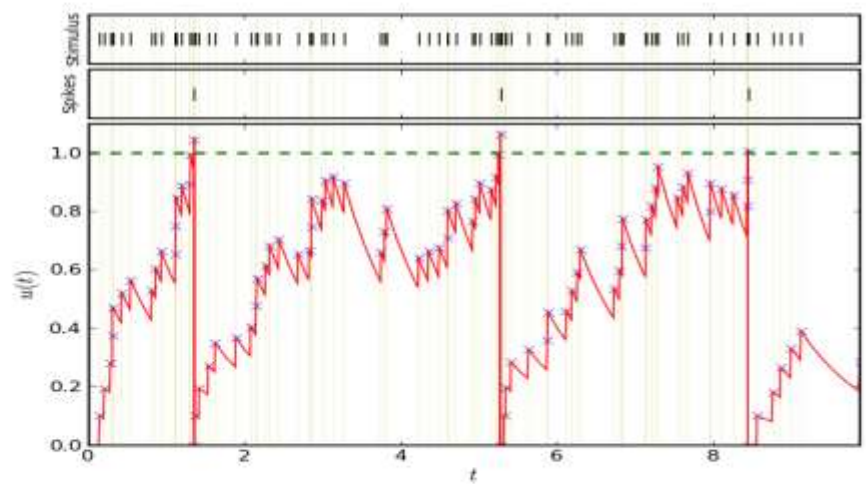
Spiking neuron models

Models of a spiking neurons and SNN

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

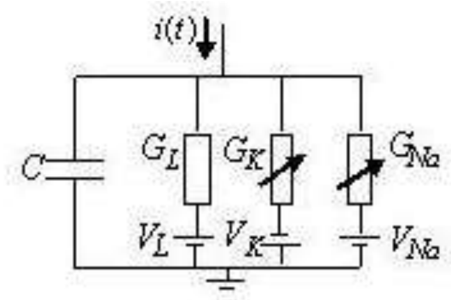






Hodgkin- Huxley Model

- A detailed description of the influences of the conductance of three ion channels on the spike activity of the giant axon of squid.
- Because of its biological relevance the model is commonly used by neuroscientists

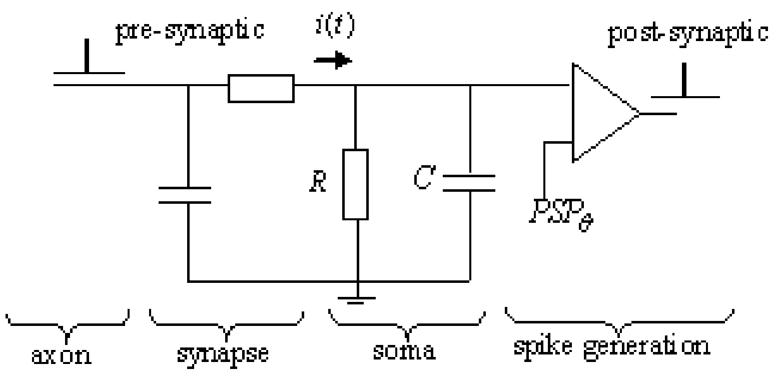


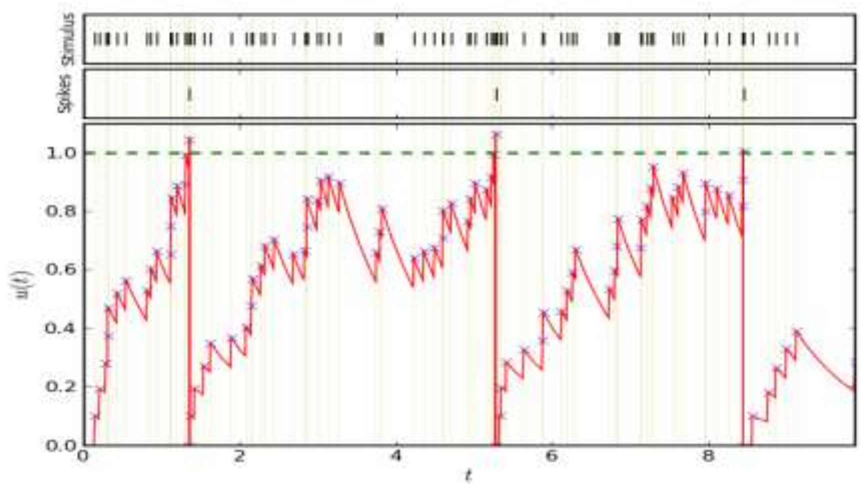
$$\sum_{ch} i_{ch}(t) = G_{Na} \times m^3 \times h \times (v_C - V_{Na}) +$$
$$G_K \times n^4 \times (v_C - V_K) + G_L \times (v_C - V_L)$$
$$\frac{dm}{dt} = \alpha_m(v_c) \times (1-m) - \beta_m(v_c) \times m$$
$$\frac{dn}{dt} = \alpha_n(v_c) \times (1-n) - \beta_n(v_c) \times n$$
$$\frac{dh}{dt} = \alpha_h(v_c) \times (1-h) - \beta_h(v_c) \times h$$

- G_{Na}, G_K and G_L - conductance of the sodium, potassium and leakage channels
- V_{Na}, V_K and V_L are constants called reverse potentials,
- *m* and *n* control the N_a channel and variable *h* controls the *K* channel
- *α* and *β* are empirical functions of v_c

Leaky Integrate-and-Fire Neuronal Model

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





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

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

Spike Response Model

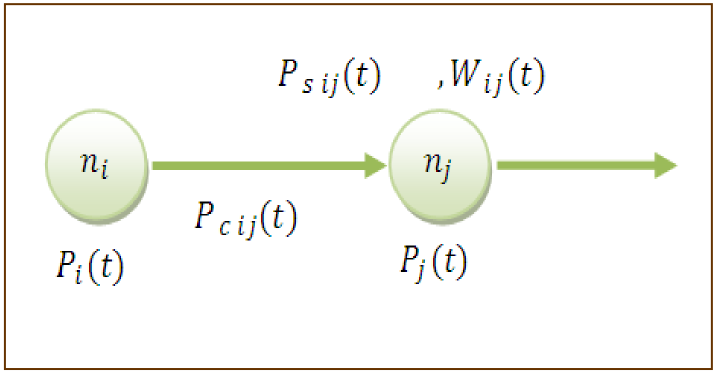
- Generalization of the LIF model, introduced by Gerstner et. al. in 1993
- State of a neuron described by a single variable *u*
- Incoming spikes perturb *u*, which is modeled by a kernel function **ε**
- If *u* reaches a threshold value ϑ , a spike is triggered
- Shape of an action potential and the after potential is modeled by a second kernel function **η**

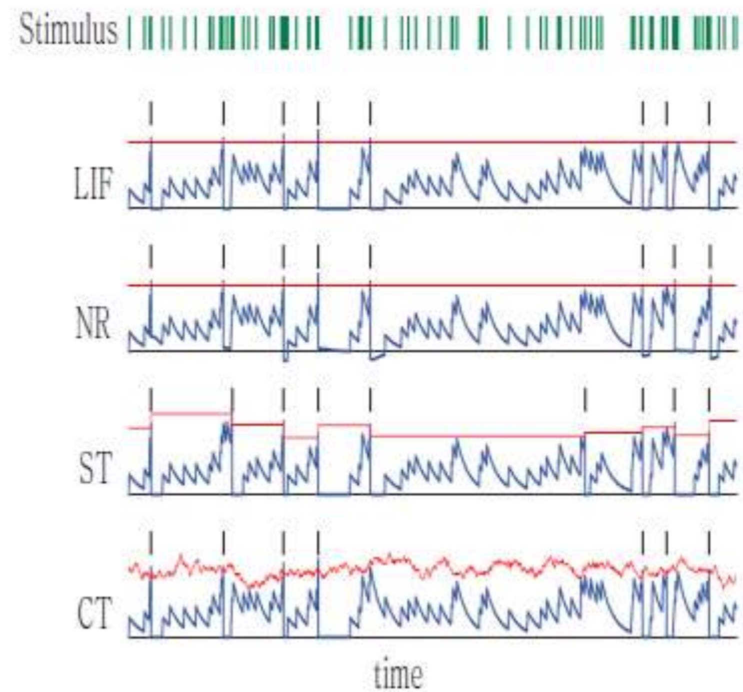
$$u_i(t) = \eta(t - \hat{t}_i) + \sum_j w_{ij} \sum_f \varepsilon_{ij}(t - \hat{t}_i, t - t_j^{(f)})$$

- $t_j^{(f)}$ are firing times of pre-synaptic neurons j, w_{ij} is the synaptic weight
- $\hat{t}_i$ is the time of the last output spike of neuron i

A probabilistic spiking neuron model

(N. Kasabov, To spike or not to spike: A probabilistic spiking neuron model, Neural Networks, Jan. 2010)





The information is represented as connection weights and probabilistic parameters.

The PSPi(t) is calculated using a formula:

$$PSP_i(t) = p_i(t) \sum_{p=t_0,..,t} \sum_{j=1,..,m} e_j \, g(p_{cj,i}(t-p)) \, f(p_{sj,i}(t-p)) \, w_{j,i}(t) - \eta(t-t_0)$$

As a special case, when all probability parameters are “1”, the model is reduced to LIF model.

Neural Model by Izhikevich

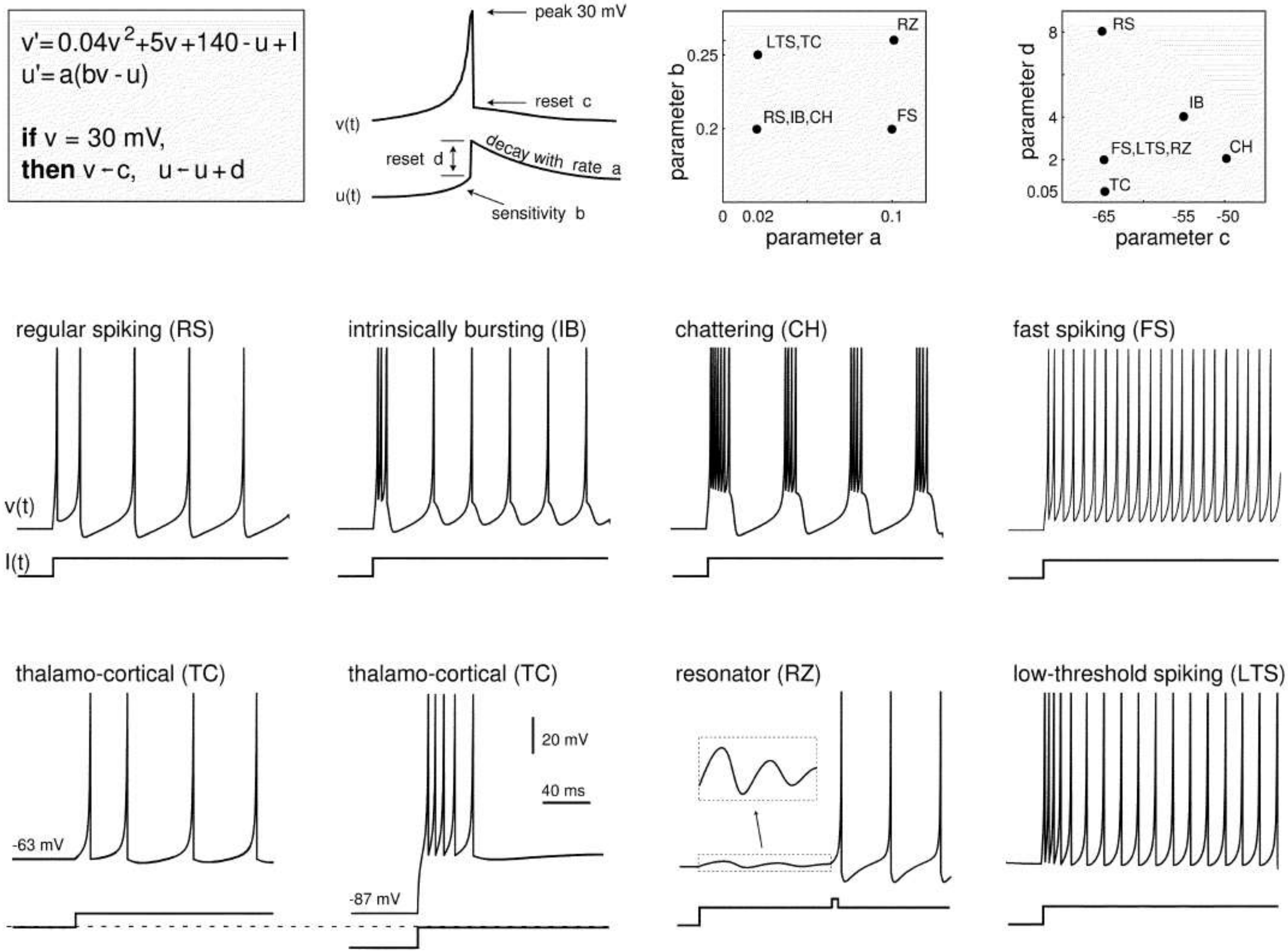
- Model claims to be as biological plausible as the HH model with computational efficiency of LIF models
- Depending on its parameter configuration the model reproduces different spiking and bursting behavior of cortical neurons

$$
\begin{aligned}
v' &= 0.04v^2 + 5v + 140 - u + I \\
u' &= a(bv - u)
\end{aligned}
$$

$$
\text{if } v \geq 30\text{mV, then} \begin{cases} v & \leftarrow & c \\ u & \leftarrow & u + d \end{cases}
$$

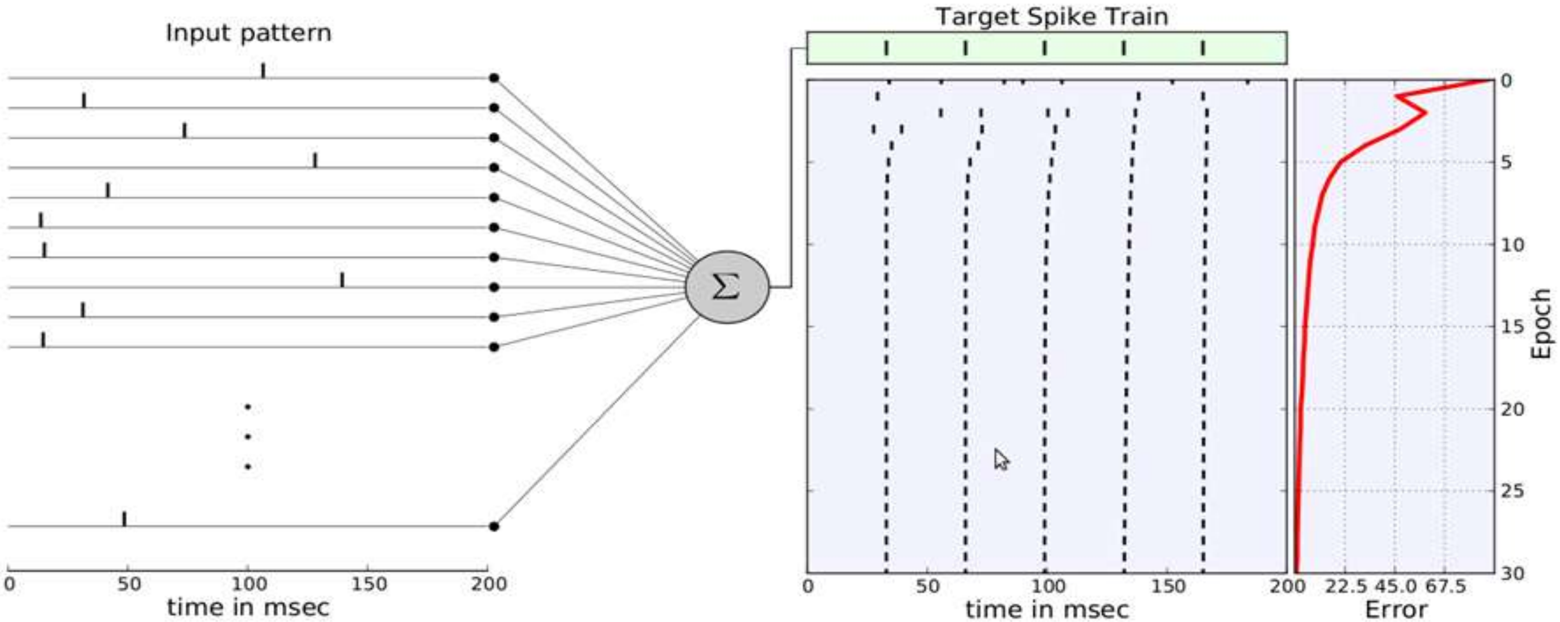
- a,b,c,d are parameters of the model, v represents the membrane potential, u the membrane recovery

Dynamics of the Izhikevich Model



Spike Pattern Association Neurons: SPAN

(Mohemmed,A., Schliebs,S., Kasabov,N. SPAN: Spike Pattern Association Neuron for Learning Spatio-Temporal Sequences, Int. J. Neural Systems, 2012.



A single output neuron is trained to respond with a temporally precise output spike train to a specific spatio-temporal input.

Spike pattern association neuronal models: SpikeProp; ReSuMe; Tempotron; Chronotron.

SPAN delta learning rule

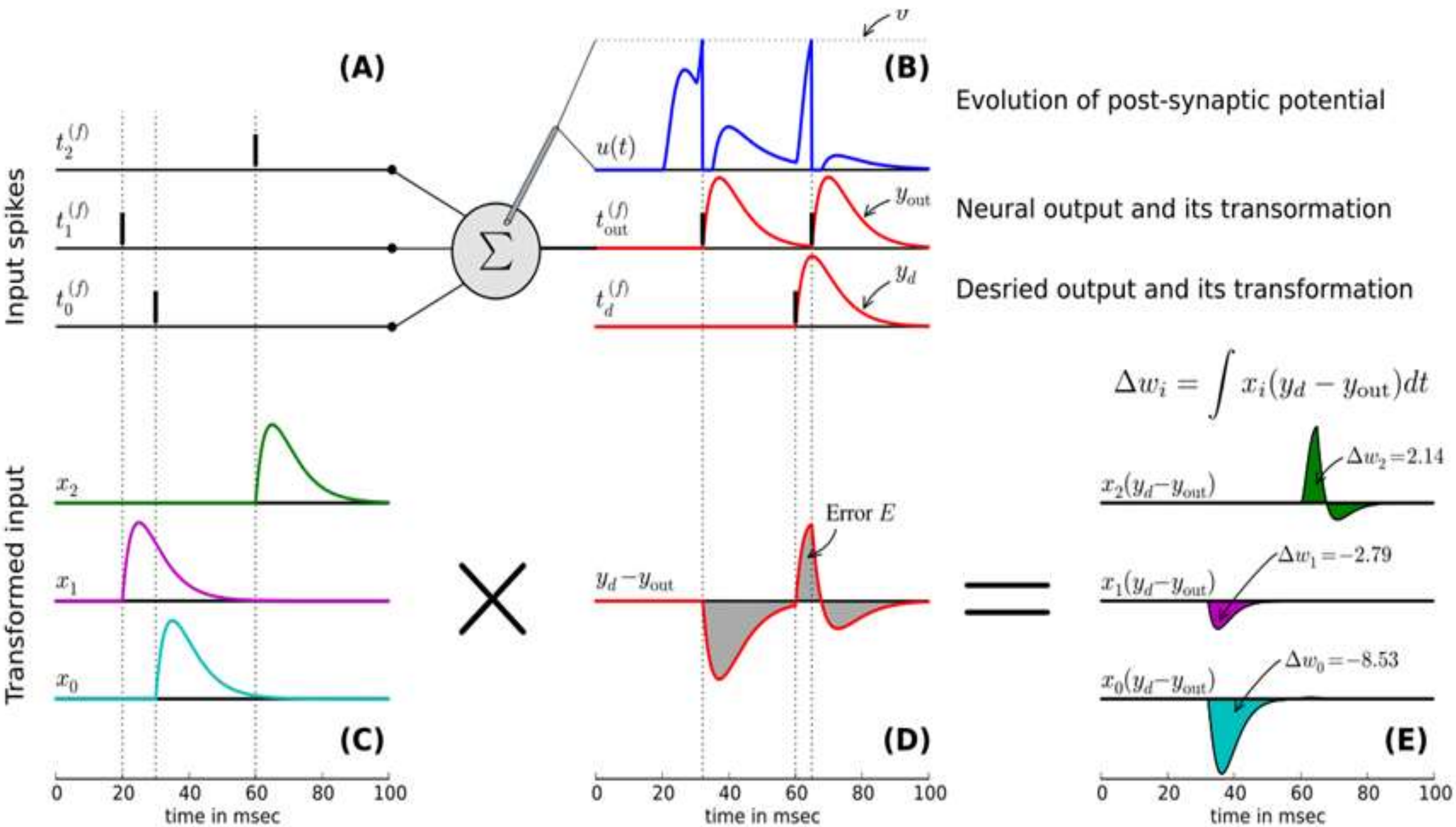
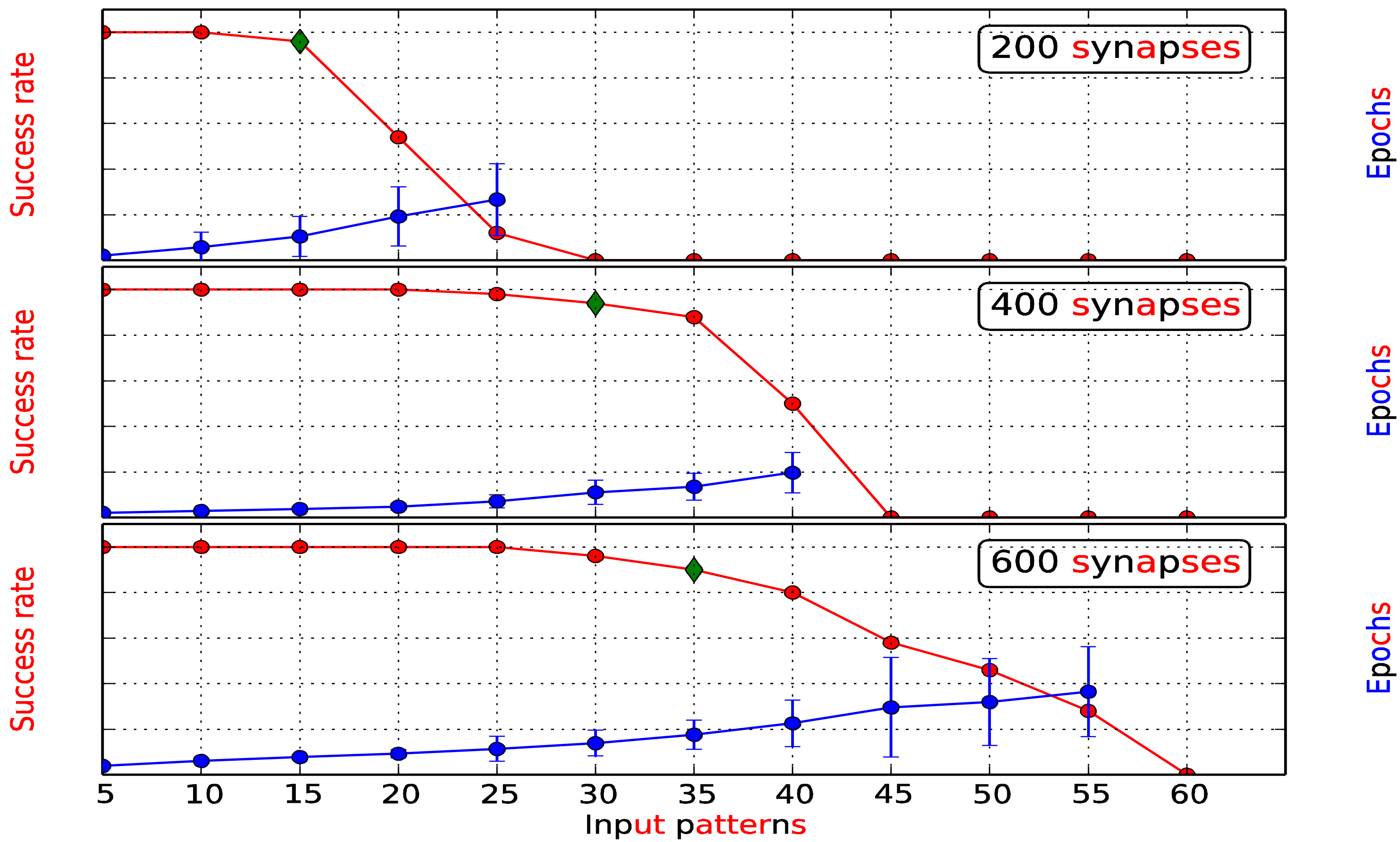


Illustration of the proposed training algorithm.

What is the memory capacity of a single SPAN?

(Mohemmed et al, Int J. Neural Systems, 2012)



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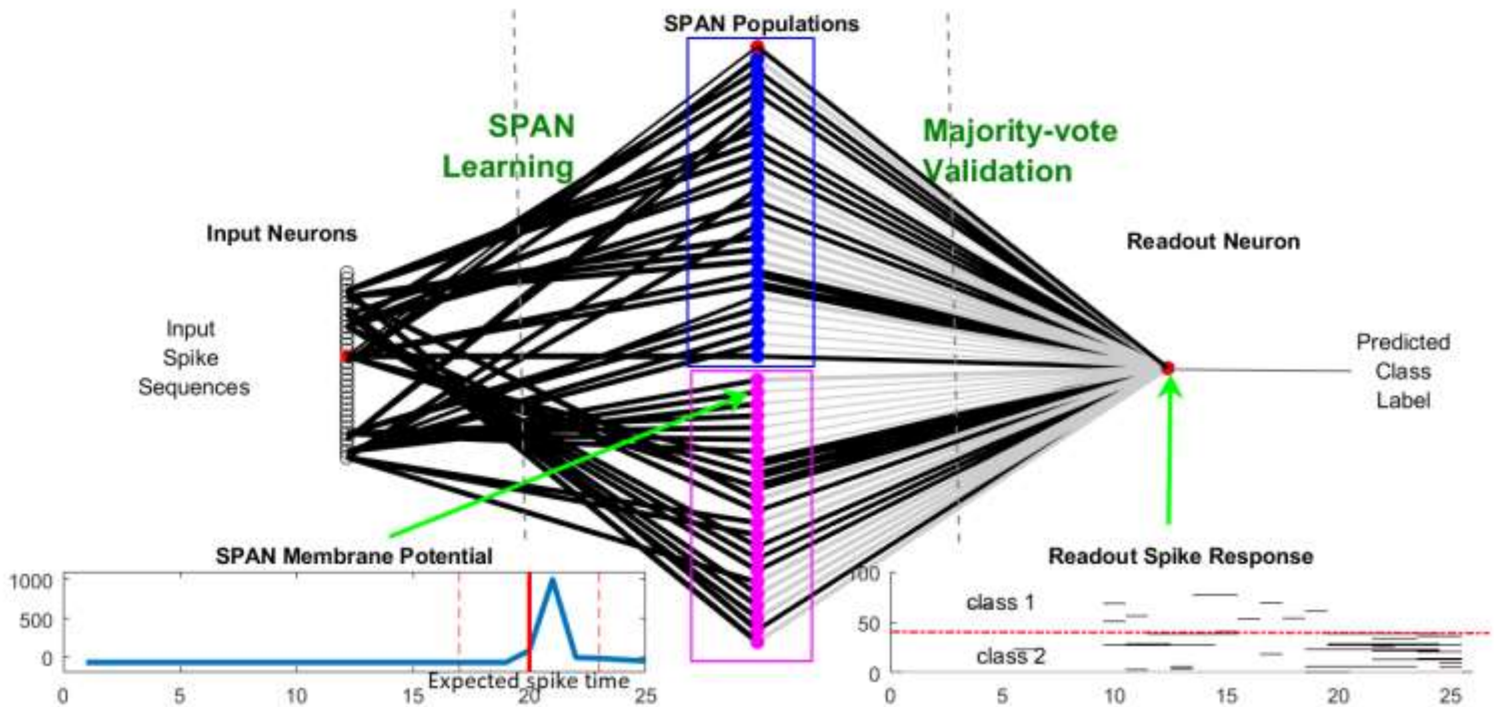
Kumarasinghe K, Taylor D, Kasabov N, ESPANNet: Evolving Spike Pattern Association Neural Network for spike-based supervised incremental learning and its application for single-trial Brain Computer Interfaces, , International Joint Conference on Neural Networks, Budapest, 14 Jul 2019 - 19 Jul 2019. Proceedings of the 2019 International Joint Conference on Neural Networks. 2019, **DOI:**10.1109/IJCNN.2019.8852213

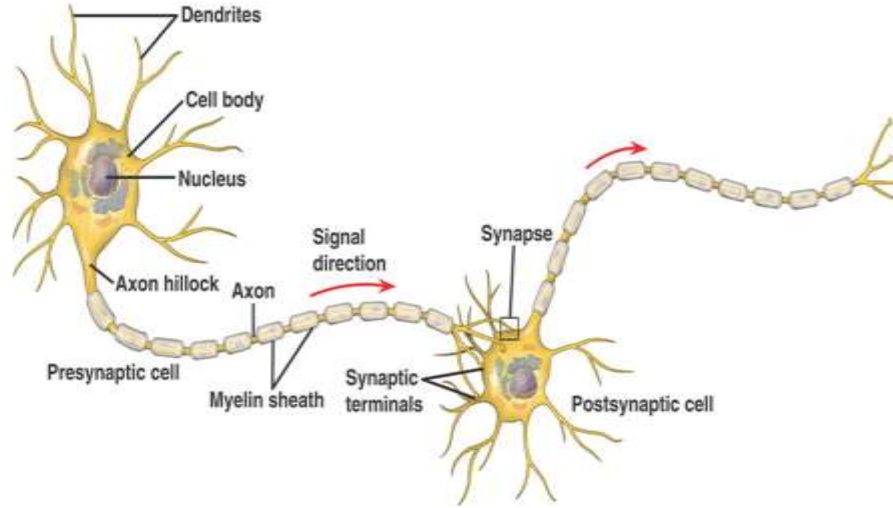


A single input synapse-based eSPANNet model trained and validated using movement intention and resting-state EEG signals of data from a single participant. Synaptic learning was performed using SPAN learning rule with training spike sequences. The network was validated using majority-vote of SPAN's for the validation dataset. Grey-coloured synapses between SPAN's and readout neuron returned a lower correct rate than the expected threshold level and therefore not considered when evaluating the performance on the test dataset.

Methods for unsupervised learning in SNN

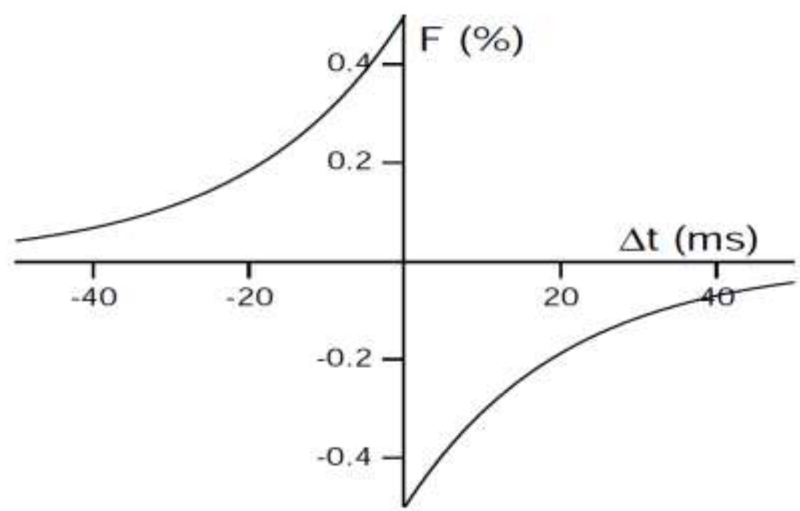
Spike-Time Dependent Plasticity (STDP)
(Abbott and Nelson, 2000).

- 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



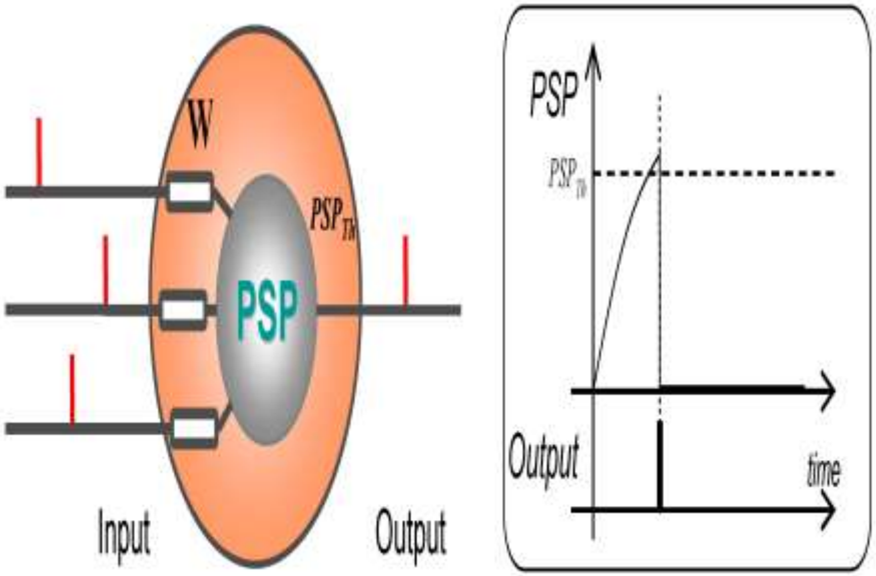
Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD:

$\Delta t = tpre - tpost$



Methods for supervised learning in SNN

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



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

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

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

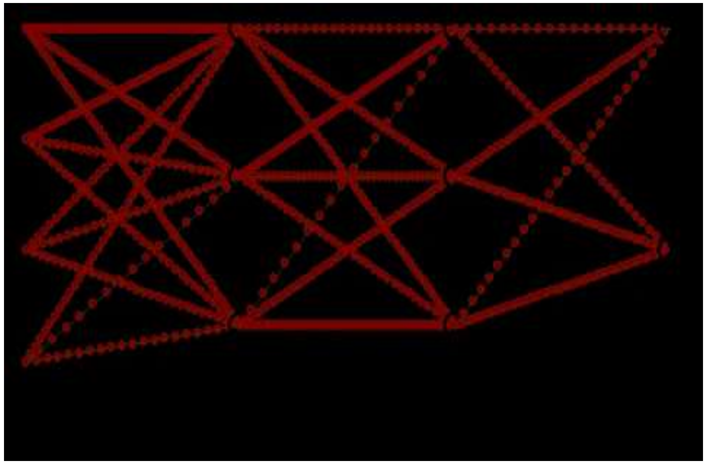
PSP_{Th}=C. PSPmax (T)

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

Spiking neural network architectures: From local neuronal learning to global knowledge representation through building connectivity

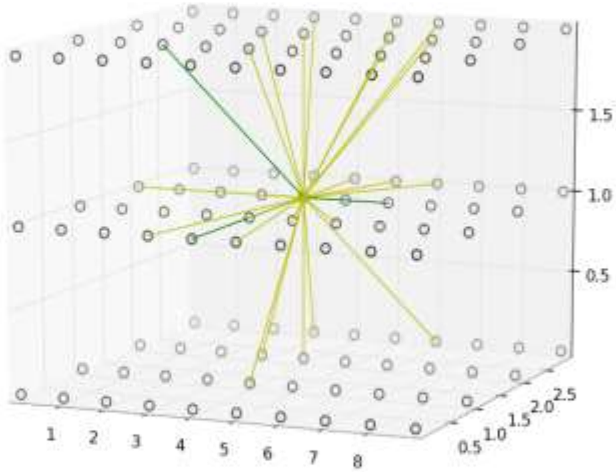
Generic SNN structures:

- Feedforward
- Recurrent
- Evolving
- Convolutional
- Reservoir
- Liquid sate-machines

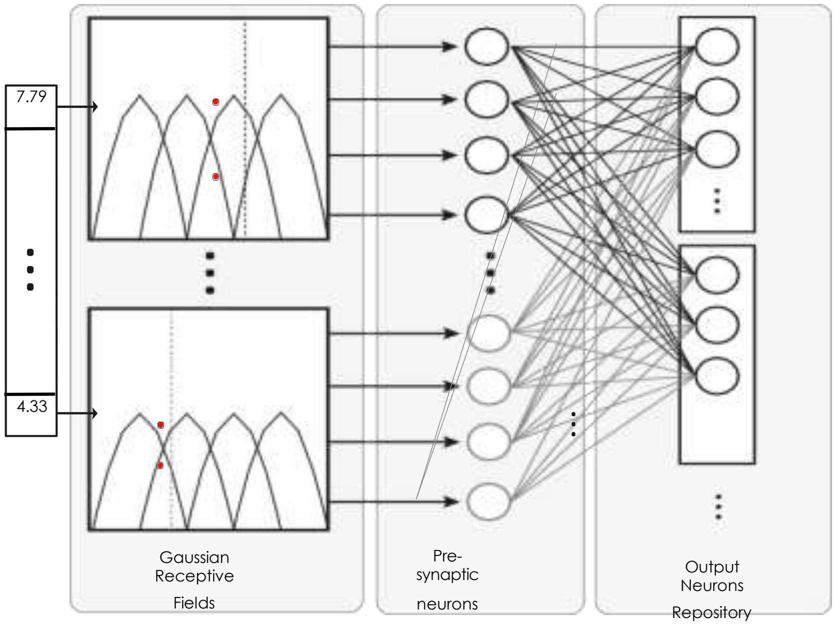


Task oriented structures:

- Classification
- Regression
- Prediction



Evolving Spiking Neural Networks (eSNN)



Kasabov, Evolving connectionist systems, Springer, 2007

Kasabov, N. Evolving connectionist systems for adaptive learning and knowledge discovery: Trends and Directions, Knowledge Based Systems, 2015, (2015), http://dx.doi.org/10.1016/j.knosys.2014.12.032.

Kasabov, N., Dhoble, K., Nuntalid, N., & Indiveri, G. (2013). Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. Neural Networks, 41, 188-201 (236 citations).

J. L. Lobo, J. Del Ser, A. Bifet, N. Kasabov, Spiking Neural Networks and online learning: An overview and perspectives, Neural Networks, 121 (2020), 88-110, https://doi.org/10.1016/j.neunet.2019.09.004

J. L. Lobo, I.Laña, J. Del Ser, M.N.Bilbao, N.Kasabov Evolving Spiking Neural Networks for online learning over drifting data streams, Neural Networks, 108, 1-19 (2018).

Jesus L. Lobo, Izaskun Oregi, Albert Bifet, Javier Del Sera, Exploiting the Stimuli Encoding Scheme of Evolving Spiking Neural Networks for Stream Learning, Neural Networks, 2019

Evolving SNN (eSNN)

- ECOS: Evolving clusters as evolving neurons and functions (Kasabov,1998)
- eSNN: ~ for spiking neurons (Wysoski, Benuskova, Kasabov, 2006-2010);
- Uses the first spike principle (Thorpe et al.) for fast on-line training
- For each input vector

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

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

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

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

Weights change based on the spike time arrival

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

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

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

  d) Update the corresponding threshold ϑ:

$$\vartheta \Leftarrow \frac{\vartheta_{new} + N\vartheta}{1+N}$$

- Schliebs, S. and N.Kasabov, Evolving spiking neural networks: A Survey, *Evolving Systems*, Springer, 2013.

Evolving Connectionist Systems (ECOS)

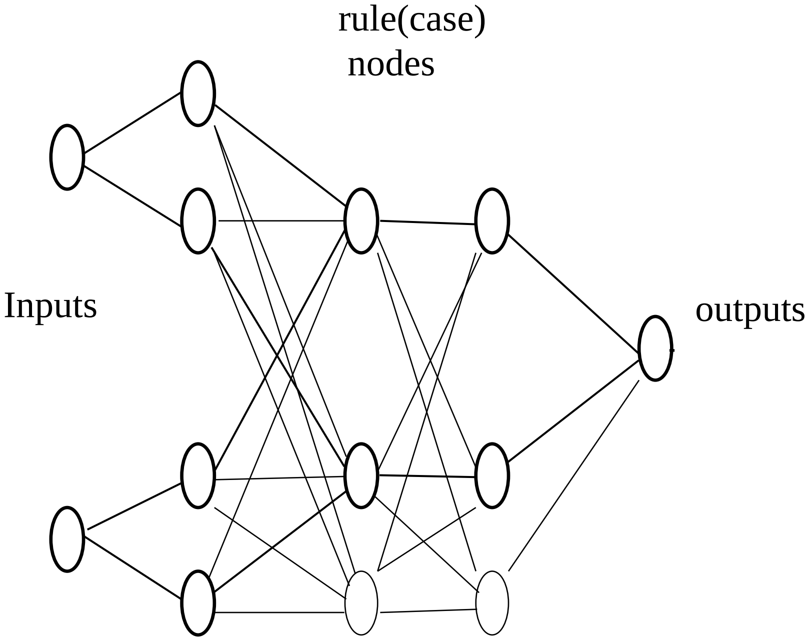
Adaptive neural networks for incremental learning and rule extraction
The neuro-fuzzy systems (no more the “black box curse”)

- Evolve their structure and functionality.
- Knowledge-based !!

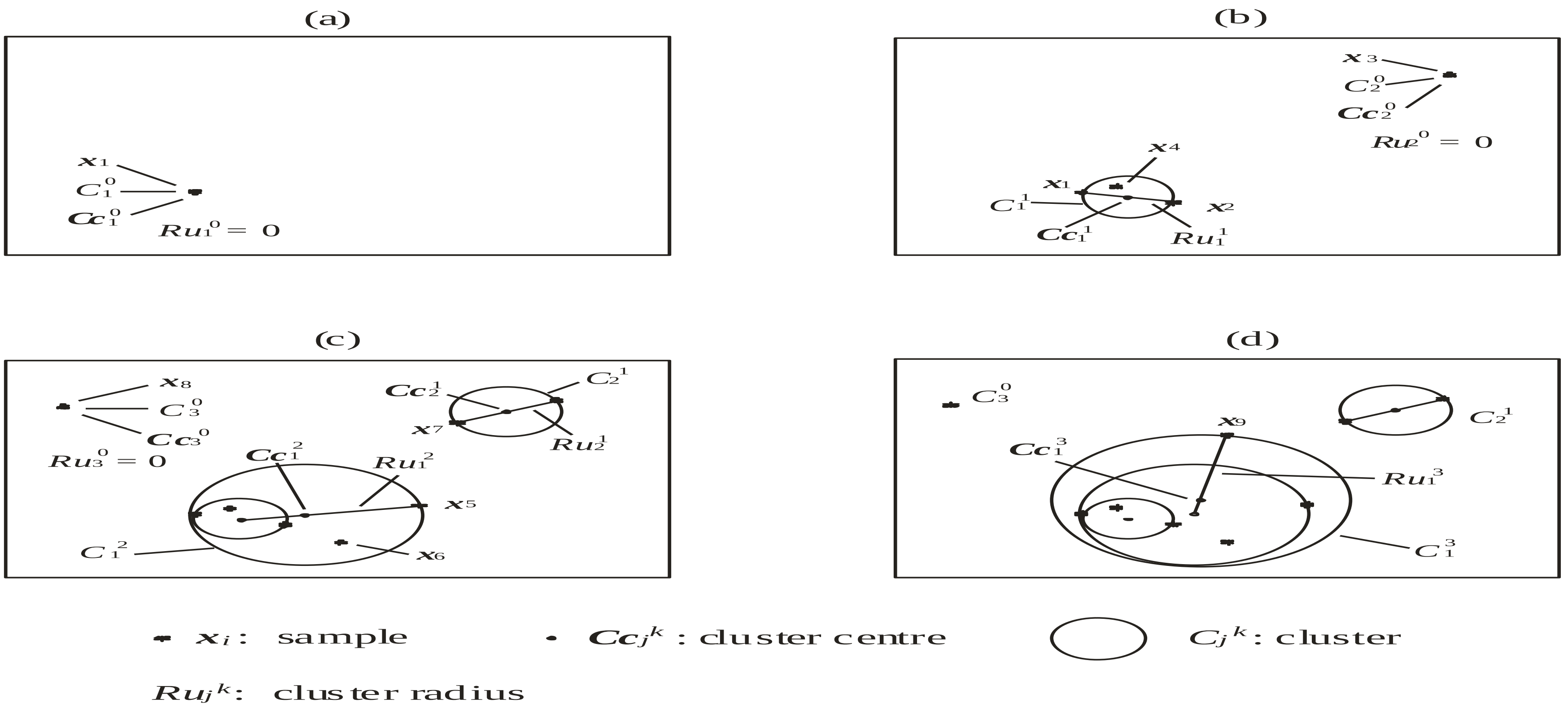
- Neuro-fuzzy systems
- As a general case, input and/or output variables can be non-fuzzy (crisp) or fuzzy
- Fuzzy variables, e.g. Gaussian MF
- Early works:
  - Yamakawa (1992)
  - EFuNN, DENFIS, N. Kasabov, 2001/2002
- Incremental, supervised clustering
- Fuzzy rules can be extracted from a trained NN and the rules can change (evolve) as further training goes:

IF Input 1 is High and Input 2 is Low
THEN Output is Very High (static knowledge)

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



Local learning based on incremental clustering of input (or input-output) vectors and learning local models



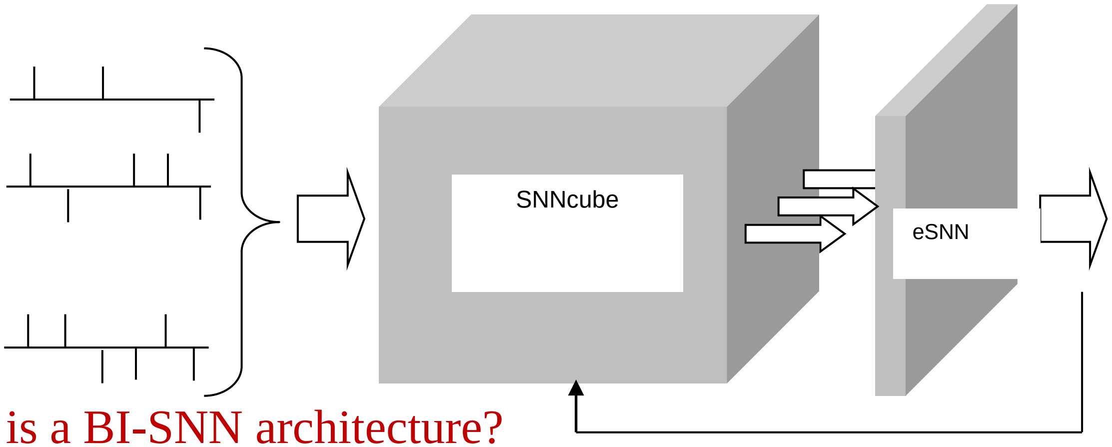
An evolving clustering process using ECM with consecutive examples x1 to x9 in a 2D space (Kasabov and Song, DENFIS, IEEE Tr FS, 2002)

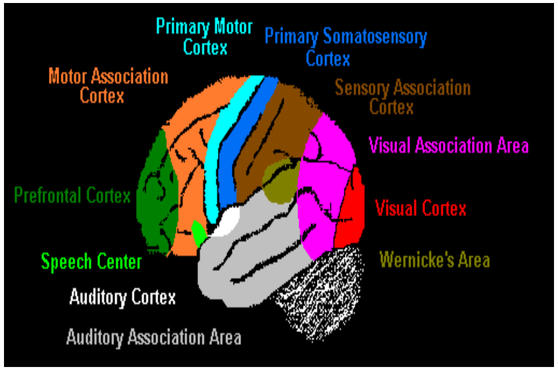
Ulster University

Comparison between statistical methods, second generation of ANN (e.g. MLP, Convolutional NN) and SNN

Method / Features	**Statistical methods (e.g. MLR, kNN, SVM)**	**Second generation ANN (e.g. MLP, CNN)**	**SNN**
Information representation	Scalars	Scalars	Spike sequences
Input data representation	Scalars, Vectors	Scalars, Vectors	Whole SSTD patterns
Learning	Statistical, limited	Hebbian rule	Spike-time dependent
Dealing with SSTD	Limited	Moderate	Excellent
Parallelisation of computations	Limited	Moderate	Massive
Hardware support	Standard	VLSI (appr. 1000 neurons)	Neuromorphic VLSI (e.g. 1bln neurons)

3.Brain-inspired SNN. NeuCube

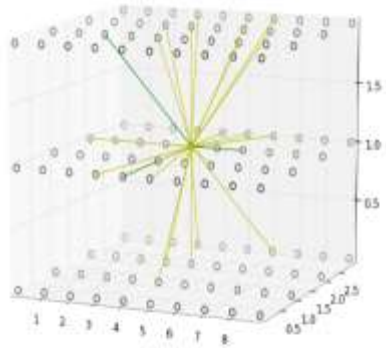




What is a BI-SNN architecture?

- 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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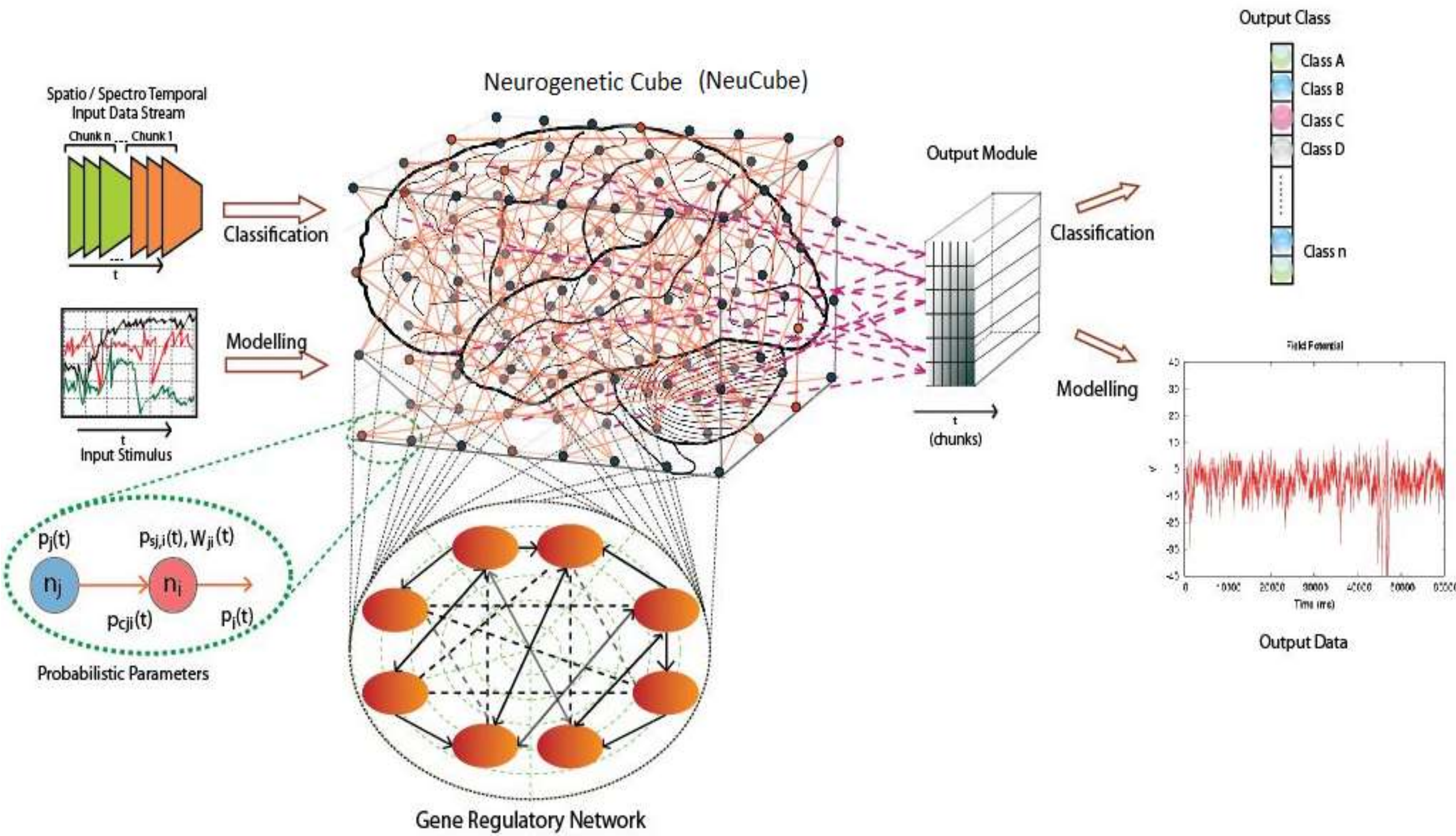
The NeuCube Architecture



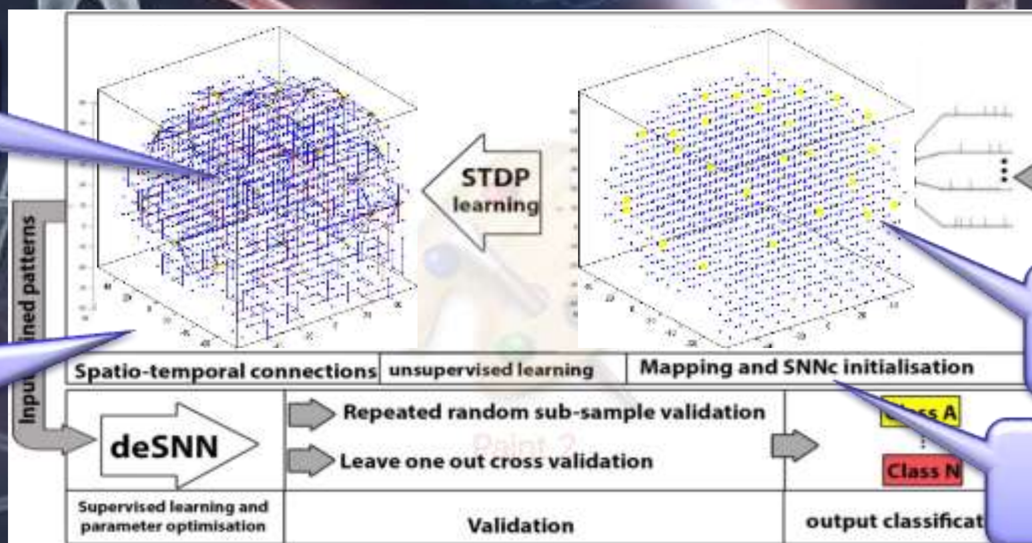
Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

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.

Deep learning in NeuCube

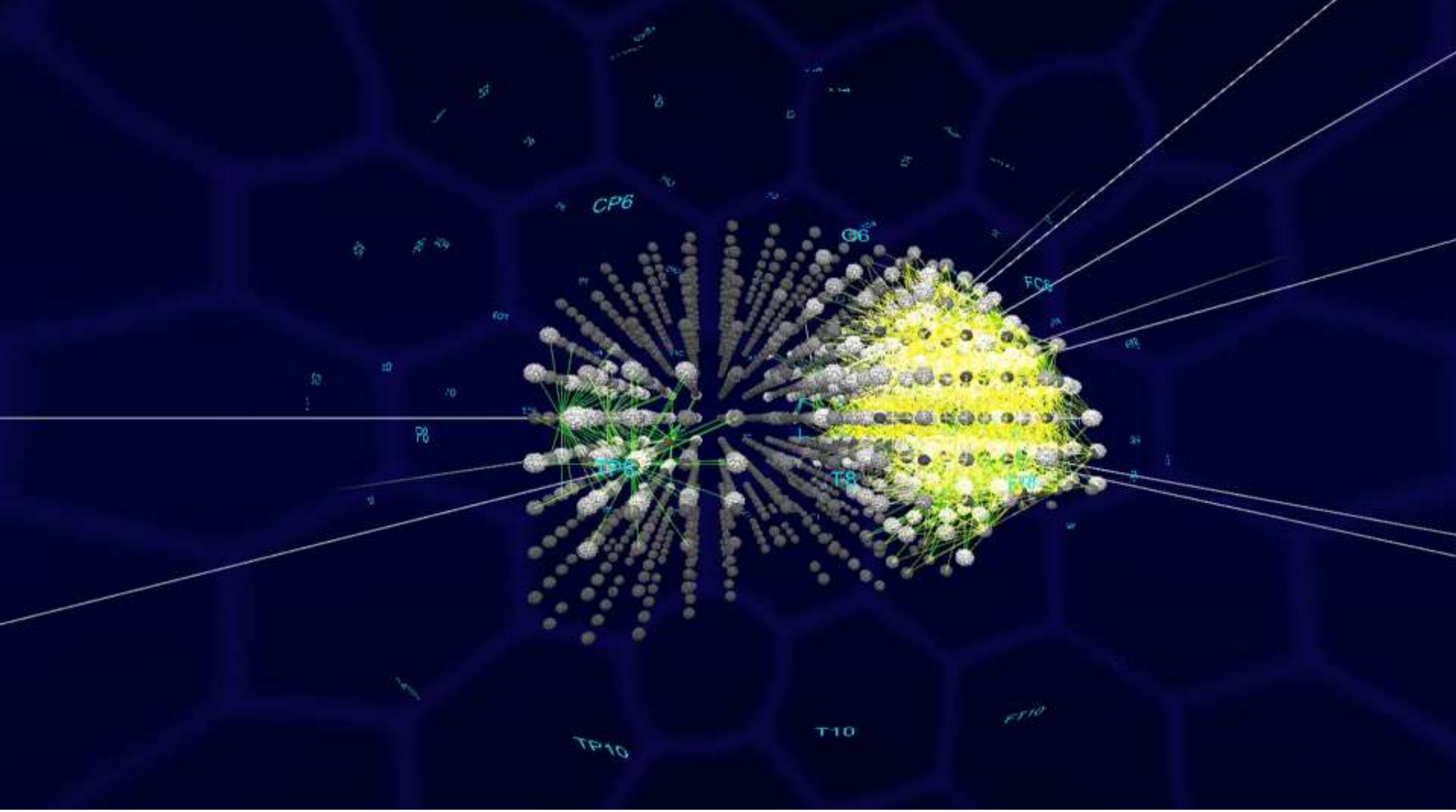
Creation of Neuron Connections During The Learning

The More Spike Transmission, The More Connections Created



Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning



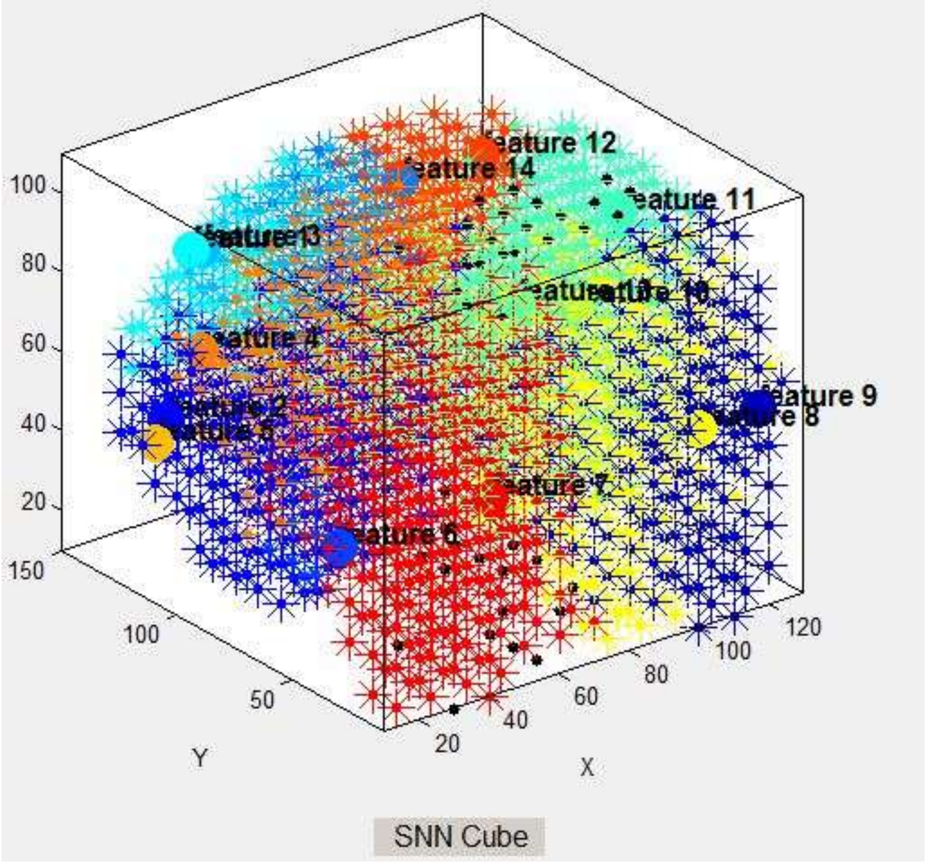
N. Kasabov, N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli,R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube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

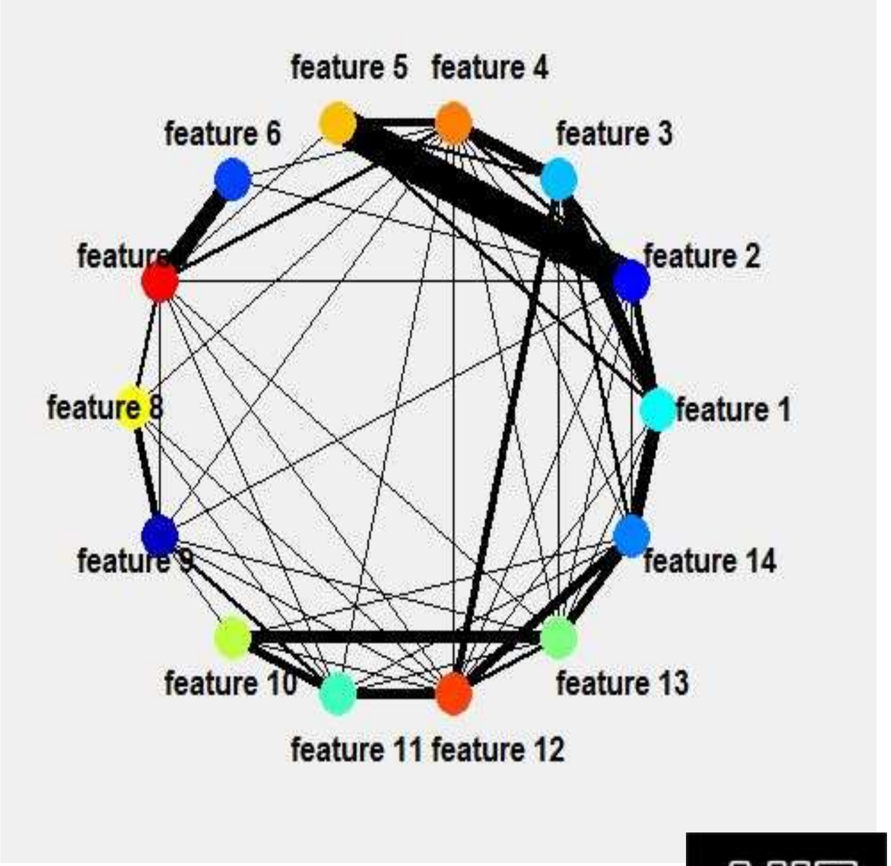
Capturing time-space knowledge as information exchange between clusters

- Clusters of highly connected neurons to input neurons;

- Clusters of spiking activity spread from input neurons ;

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





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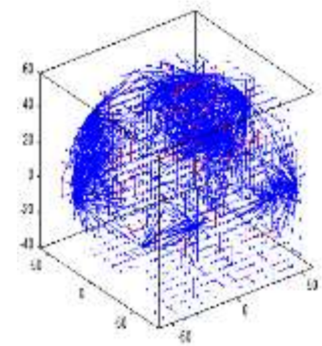
Time-Space Rule (TSR) representation in BI-SNN – “opening the cube”

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

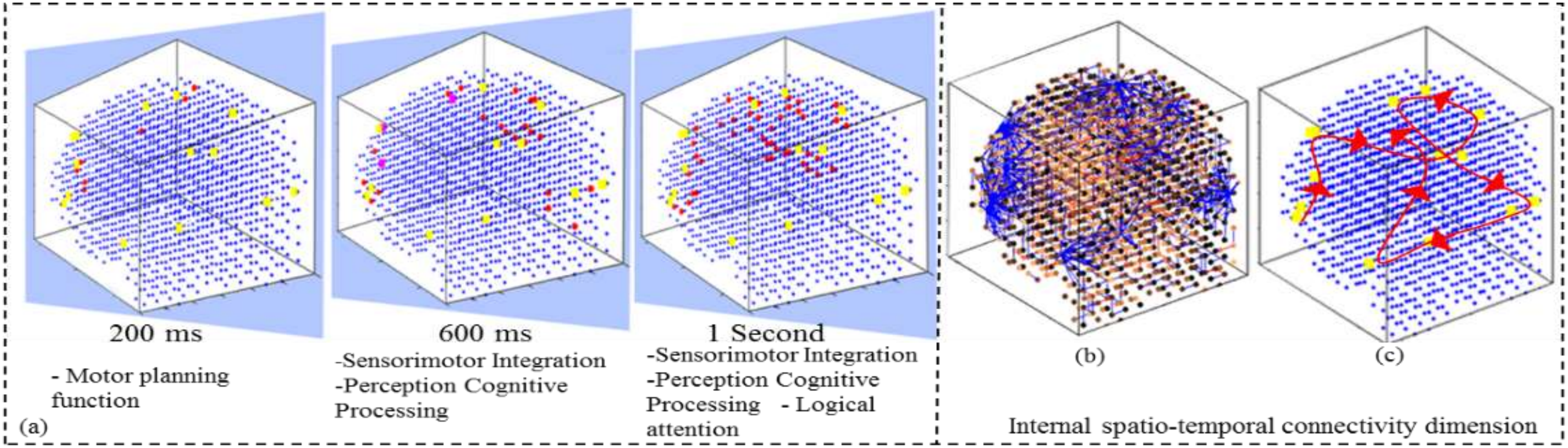
Example:

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.

Example

A SNNcube that learns EEG data from 14 EEG channels when a person is moving a hand. 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):

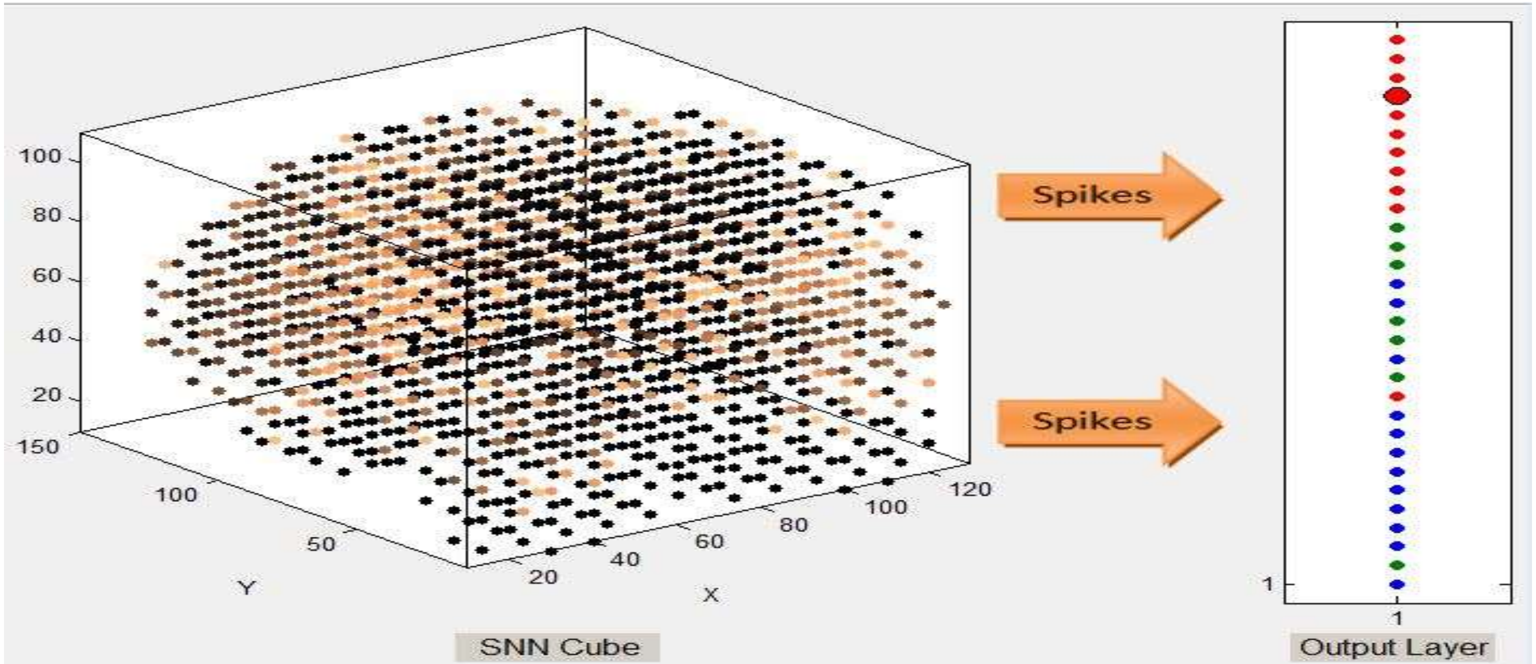
E1: Planning, in the Motor Planning functional brain area, time T1,

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.

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).

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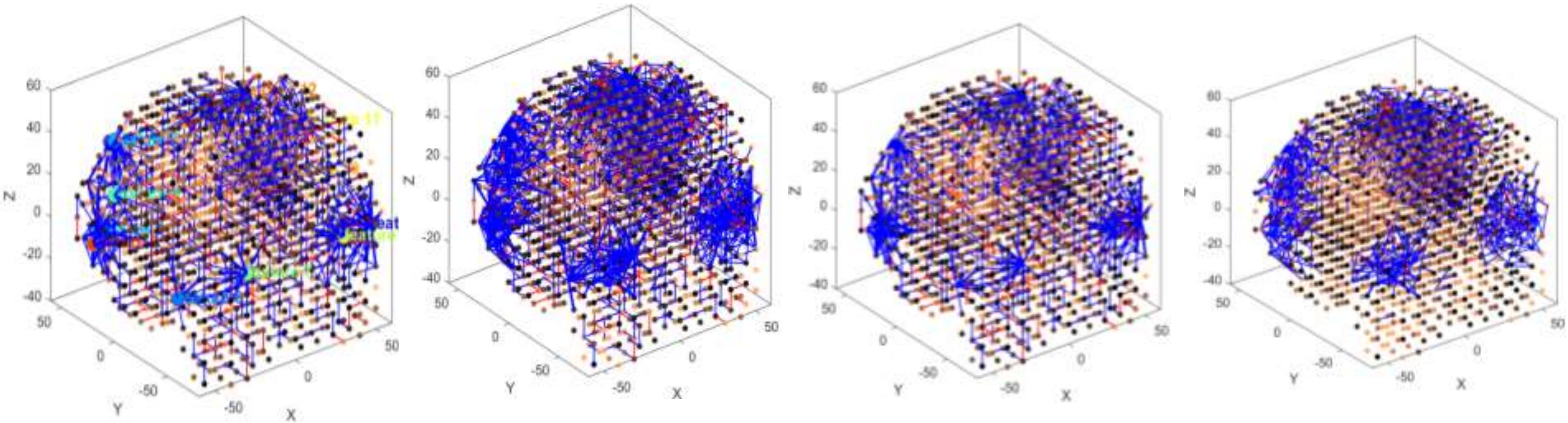
Incremental, transfer learning and knowledge evolution in BI-SNN

Example: Incremental training of NeuCube on a three class problem of EEG data of moving a wrist



(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/

Why use BI-SNN ?

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.

4. **Design and implementation of SNN systems**

Design methodology

- Analysis of the type of data and possible solutions to the problem
- SNN reservoir design according to a template (brain template or other)
- Input data transformation into spike sequences;
- Mapping input variables into spiking neurons
- Deep unsupervised learning spatio-temporal spike sequences in a scalable 3D SNN reservoir;
- Supervised learning and classification of data over time;
- Dynamic parameter optimisation;
- Model visualisation
- Extracting deep knowledge from a trained SNN
- Adaptation on new data in an on-line/ real time mode;
- Extracting of modified knowledge
- Implementation of a SNN model: von Neumann vs neuromorphic hardware systems

Analysis of the type of data and the possible solutions to the problem in hand

1. Different types of TSD:

-Temporal (e.g. climate, financial data, gene expression)
- Spatio-temporal with fixed spatial location, (e.g. brain data; seismic; GPS)
- Spatio-temporal with changing locations of the spatial variables (e.g. moving objects)
- Spectro-temporal data (e.g. radio-astronomy; audio; speech; music)

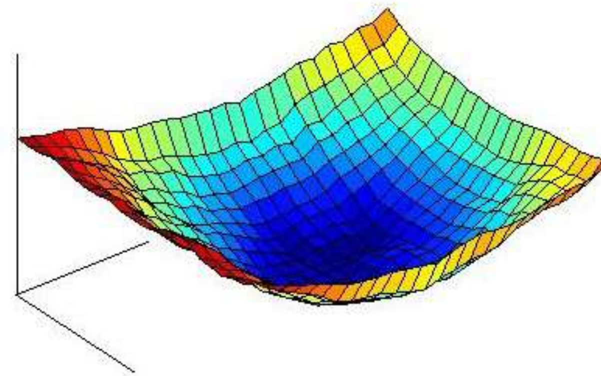
2. Different characteristics of TSD:

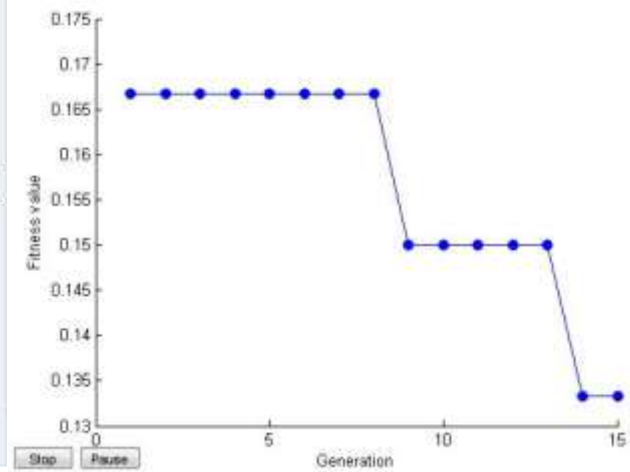
- Sparse features/low frequency (e.g. climate data; ecological data; multisensory data);
- Sparse features/high frequency (e.g. EEG brain signals; seismic data);
- Dense features/low frequency (e.g. fMRI; gene expression data);
- Dense features/high frequency (e.g. radio-astronomy data).

3. Possible solutions to the problem in hand:

- Classification;
- Prediction;
- Capturing deep, complex and meaningful time-space patterns from TSD
- Global vs Local vs Personalised modelling

NeuCube Parameter optimisation





Implementation: A NeuCube development environment

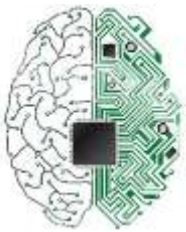
NeuCube Implementations

Software versions:

MATLAB Java python C++ Cloud

Hardware-specific versions:

RaspberryPi



Future development: NeuCube chips for AI applications

SNN Implementations on hardware platforms

From von Neuman Machines to Neuromorphic Platforms

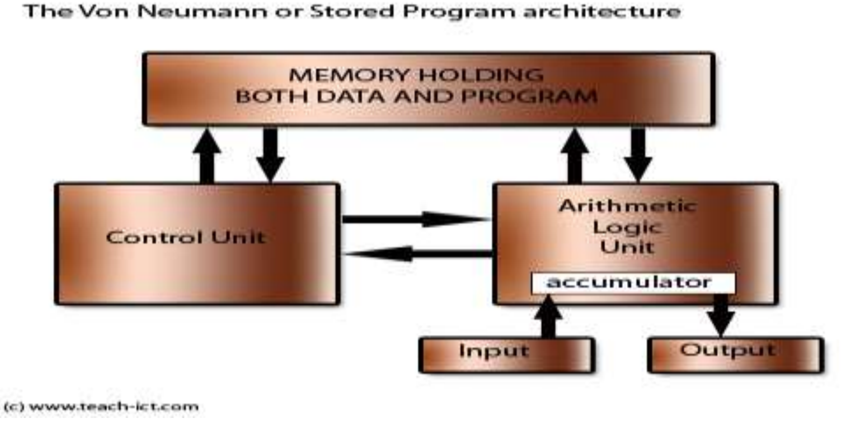
- The computer architecture of John von Neumann separates data and programmes (kept in the memory unit) from the computation (ALU); uses *bits*. First machine ABC by Atanassov and Berry.

- 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;
- Neuromorphic/Memristor architecture;
- Quantum computer (not available yet).



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

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)

High speed and low power consumption.

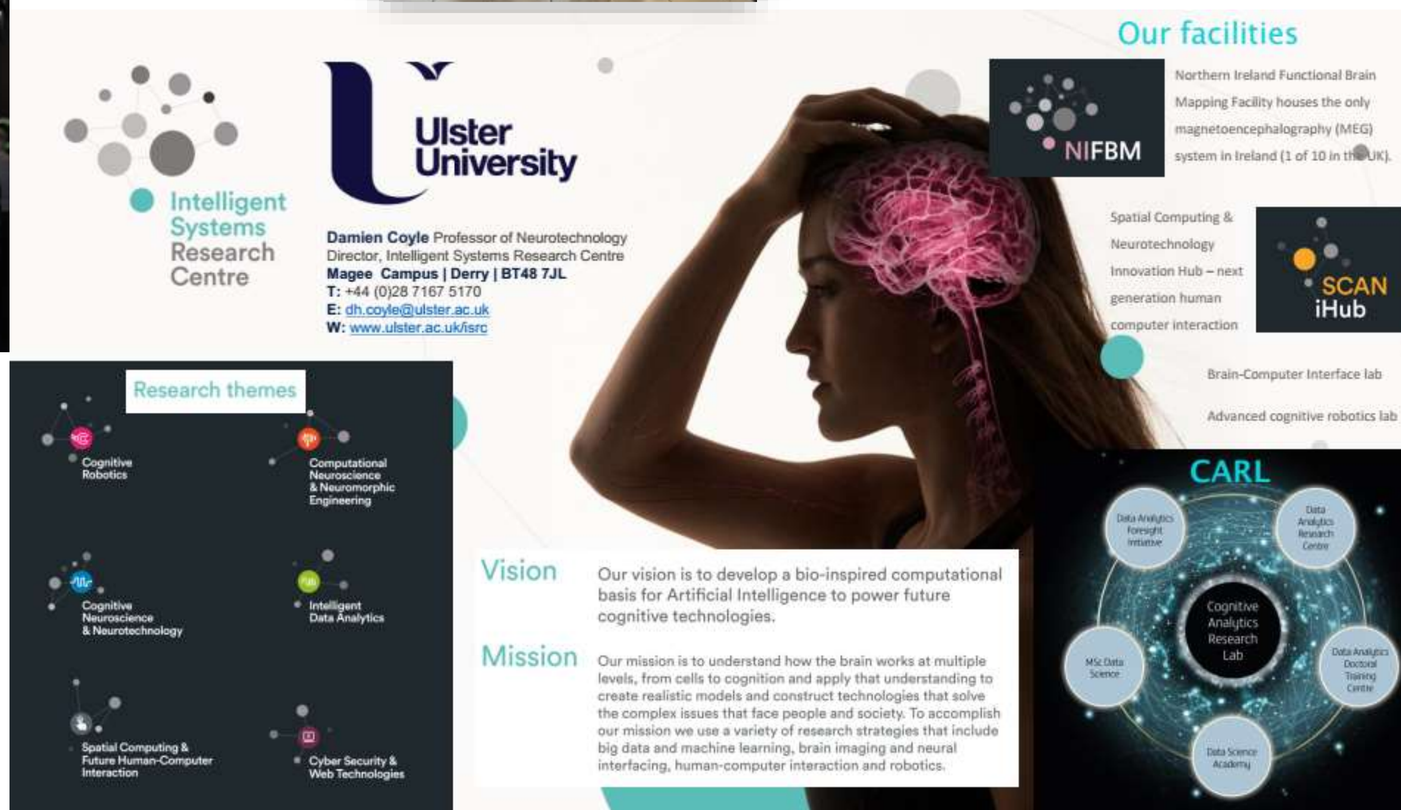
Neurotechnology and Self-Repair SNN Hardware

Intelligent Systems Research Centre, Ulster University, UK

SPANNER: A Self-Repairing Spiking Neural Network Hardware Architecture, J. Liu, J Harkin, LP Maguire, LJ McDaid, J Wade

Bio-inspired fault detection circuits based on synapse and spiking neuron models, JLiu, YHuang, YLuo, JHarkin, LMcDaid

90+ academic, post-doc, PhD researchers



5. Applications

Part IV. Brain data modelling:

Chapter 8. Deep learning and deep knowledge representation of EEG data

Chapter 9. Brain Disease Diagnosis and progmosis based on EEG data

Chapter 10. Deep learning and deep knowledge representation of fMRI data

Chapter 11. Integrating time-,space and orientation . A case study on fMRI + DTI brain data

Part V. SNN for audio-visual data and brain computer interfaces

Chapter 12. Audio and visual information processing in the brain and its modelling with eSNN

Chapter 13. Deep learning and modelling of audio and visual and multimodal audio-visual data in B

Chapter 14. Brain-computer interfaces (BCI) using BI-SNN

Part VI. SNN in Bio- and Neuroinformatics

Chapter 15. Computational modelling and pattern recognition in Bioinformatics

Chapter 16. Computational neurogenetic modelling

Chapter 17. Computational framework for personalised modelling. Applications in Bioinformatics.

Chapter 18. Personalised modelling for integrated static and dynamic data. Applications in neuroinformatics

Part VII. Application for multisensory streaming data

Chapter 19. Applications for various multisensory streaming data

Part VIII. Future development in BI-SNN and BI-AI

Chapter 20. From von Neuman machines to neuromorphic platforms

Chapter 21. From Claude Shannon's information entropy to spike-time data compression theory

Chapter 22. From brain-inspired AI to a symbiosis of human intelligence and AI

https://www.springer.com/gp/book/9783662577134

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 (best NN paper for 2016)

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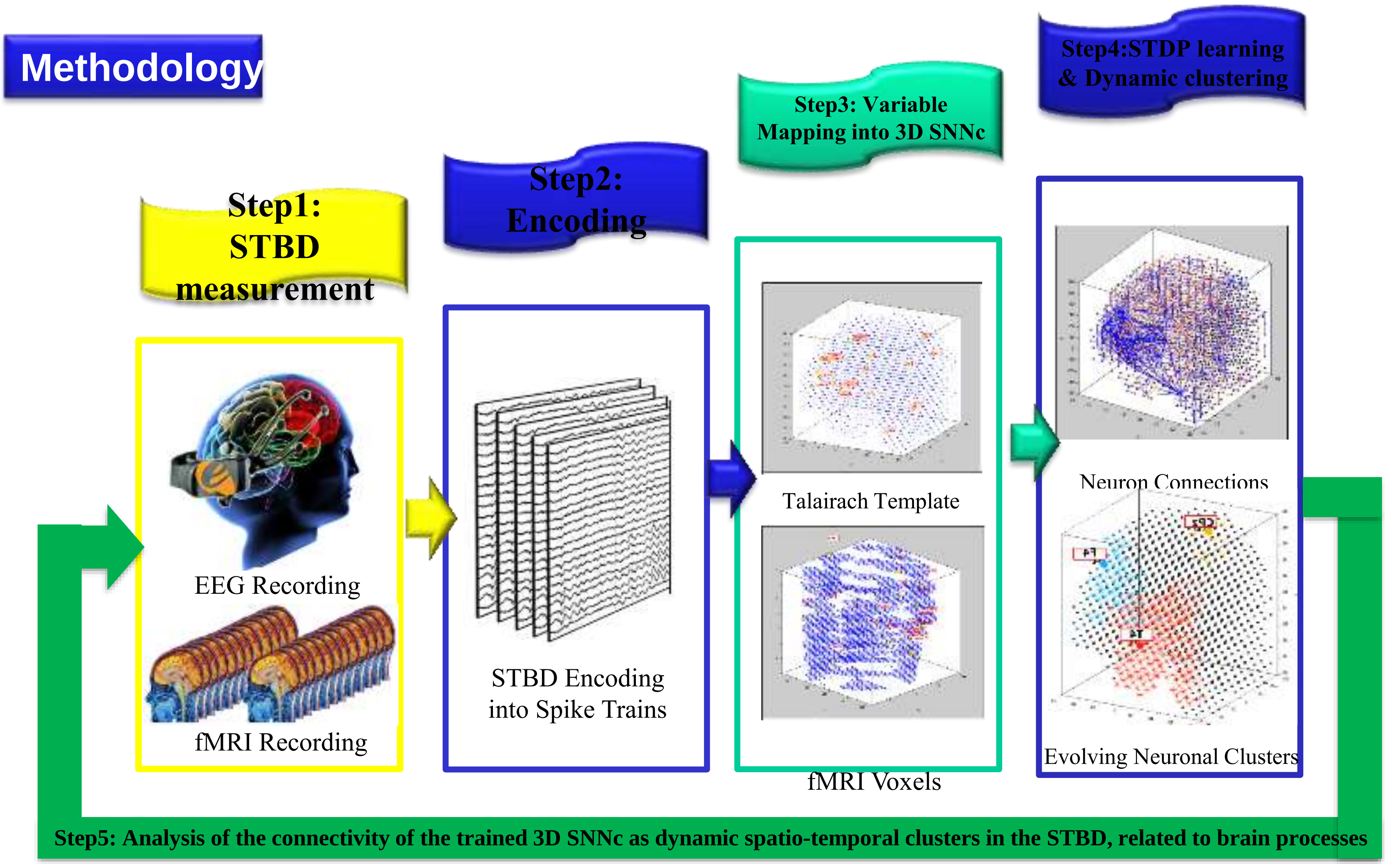
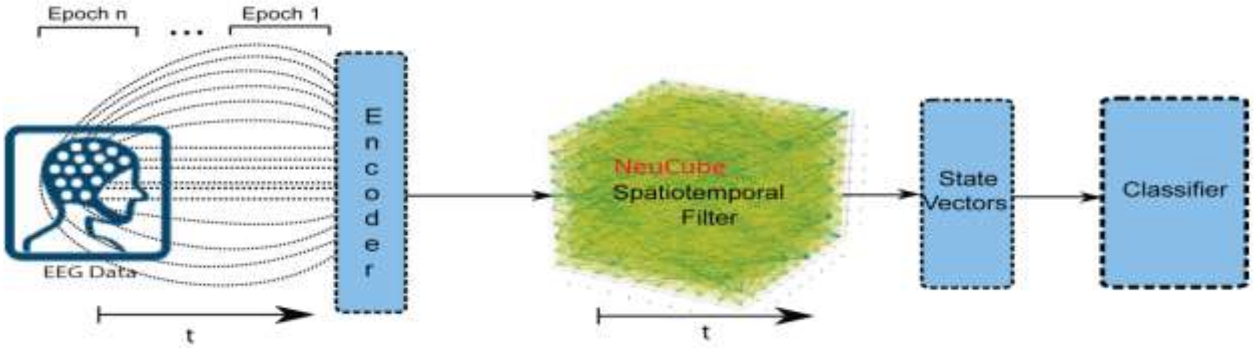
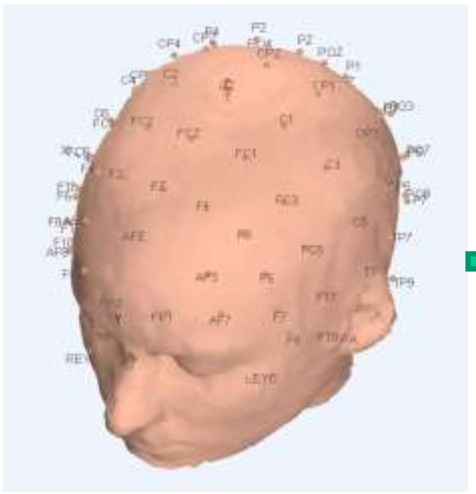
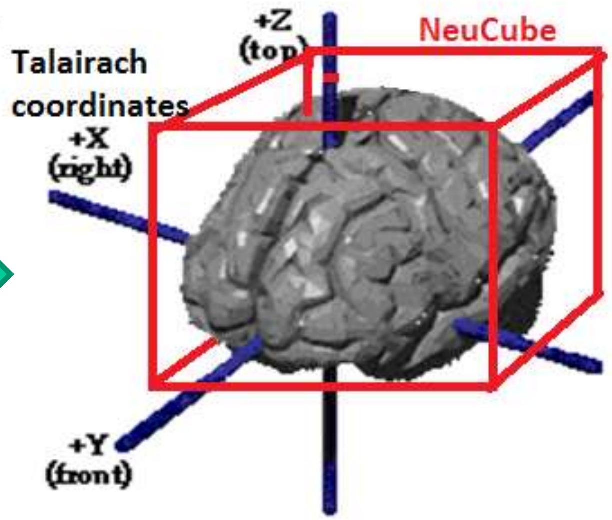
Deep learning and deep knowledge representation of brain data

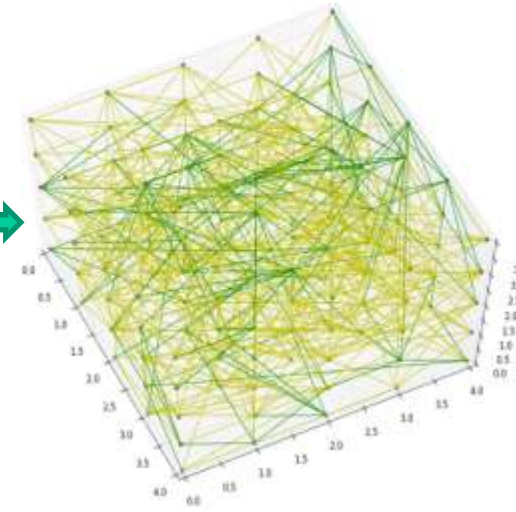


Mapping, learning and mining EEG data in NeuCube







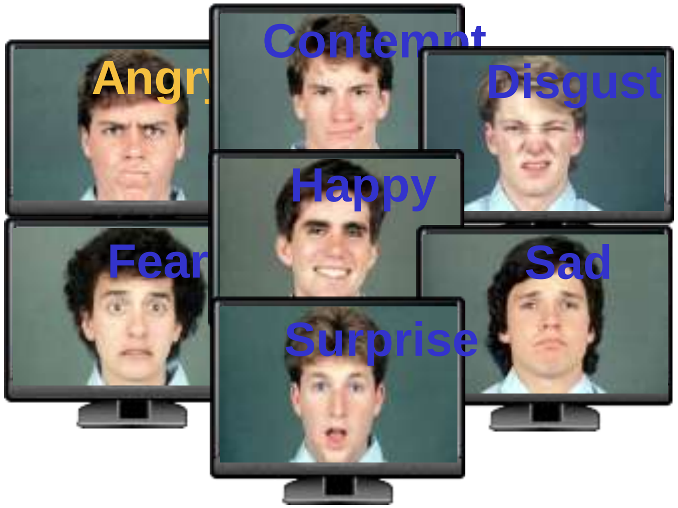


Same brain 3D coordinates (e.g. Talairach, MNI) are used for the allocated spiking neurons in the SNNc where the input data is mapped and the SNNc is analysed after training with the EEG data

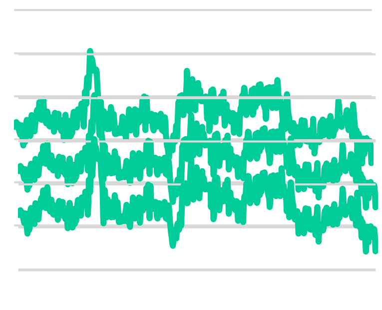
Emotional facial expression recognition and facial expression production

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

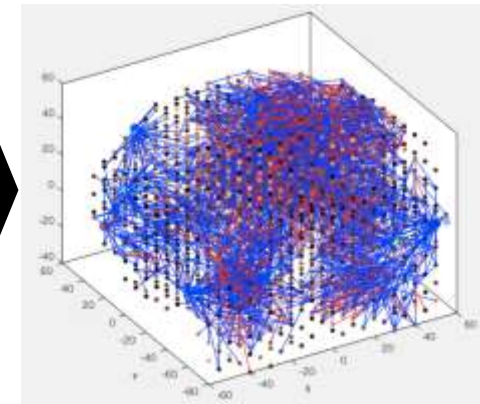
Facial Expression Perception Task



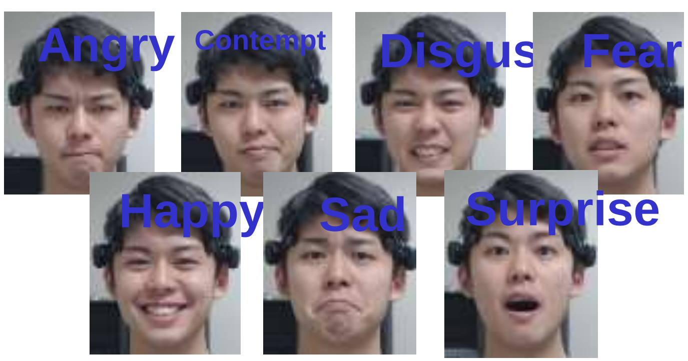
14ch EEG



94.3 %



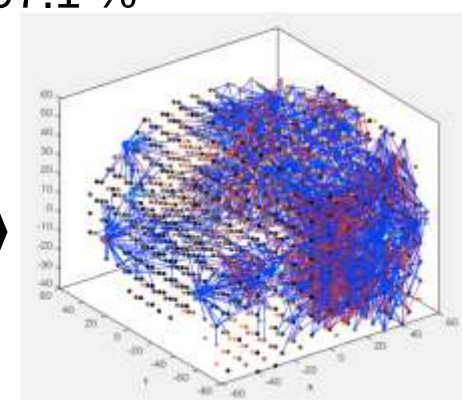
Face Expression Production Task



14ch EEG

97.1 %

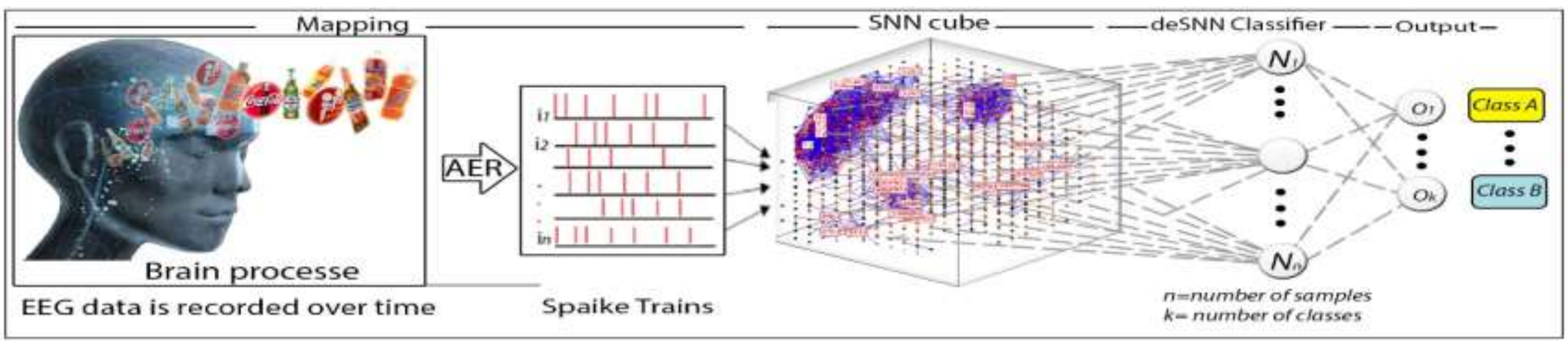
NeuCube



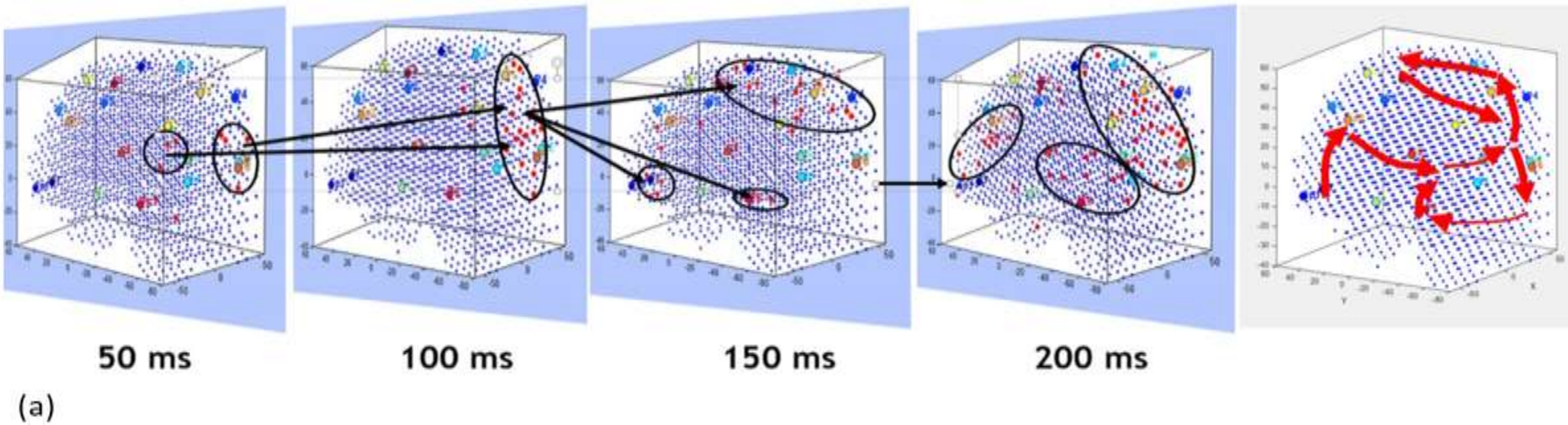
Understanding human decision making at peri-perceptual level

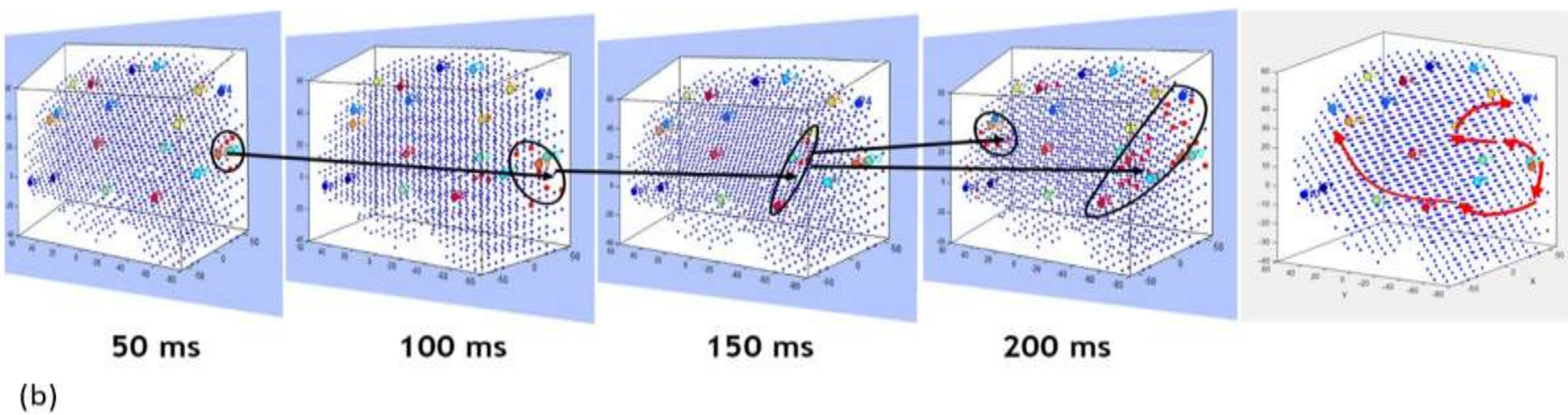
Z.Doborjeh, N. Kasabov, M. Doborjeh & Alexander Sumich**,** Modelling Peri-Perceptual Brain Processes in a Deep Learning Spiking Neural Network Architecture, ***Nature,*** Scientific REPORTS **|** (2018) 8:8912 **|** DOI:10.1038/s41598-018-27169-8; https://www.nature.com/articles/s41598-018-27169-8

Experiment: Modelling brain activity at peri-perceptual level to familiar vs non-familiar objects



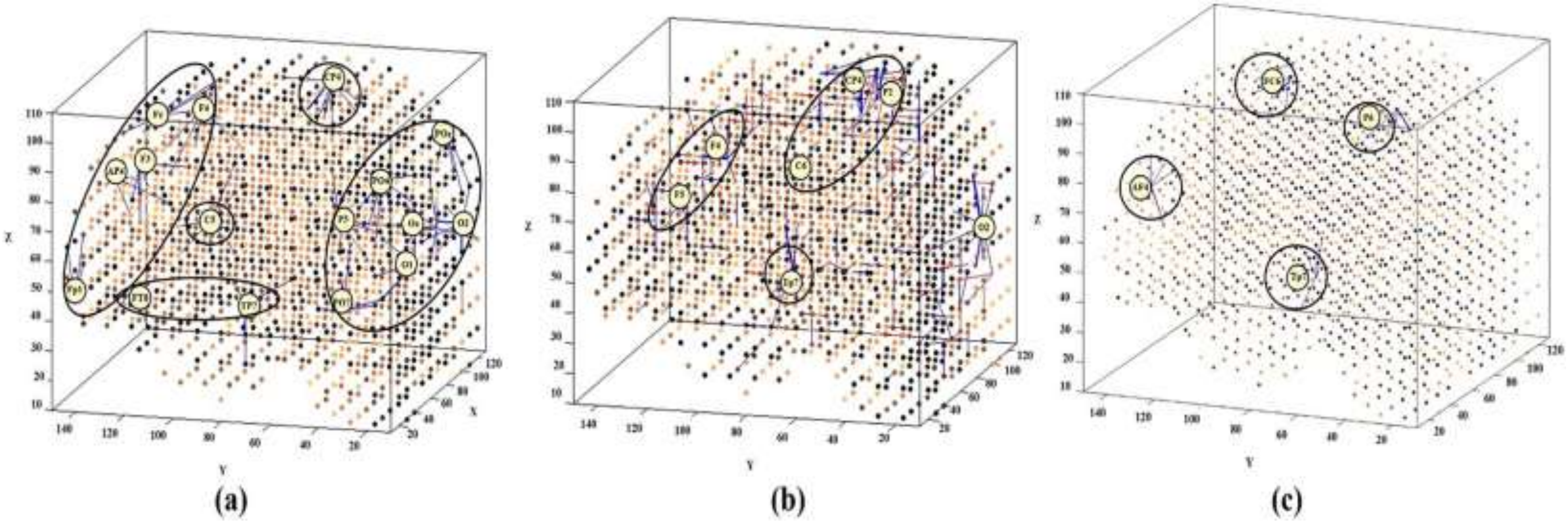
Tracing the brain dynamics in a NeuCube model





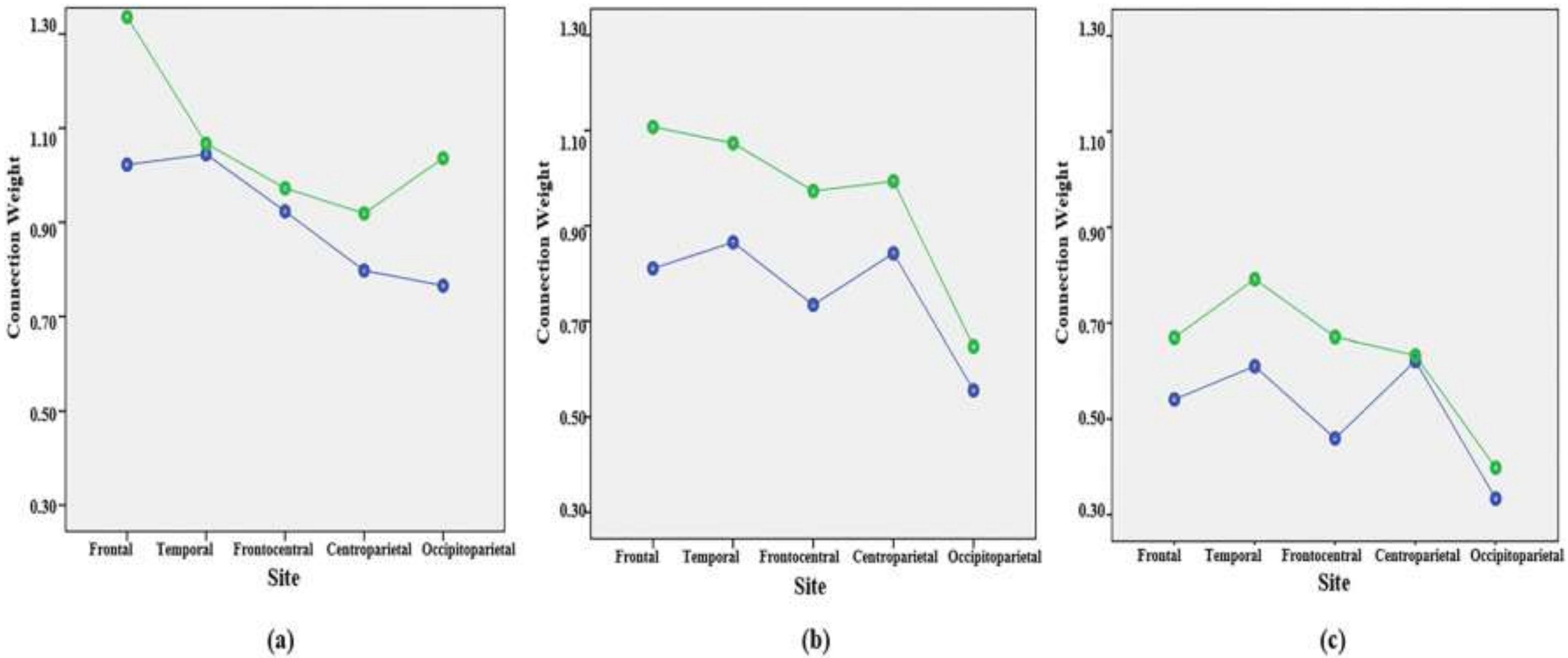
Z.Doborjeh, N. Kasabov, M. Doborjeh & Alexander Sumich**,** Modelling Peri-Perceptual Brain Processes in a Deep Learning Spiking Neural Network Architecture, ***Nature,*** Scientific REPORTS | (2018) 8:8912 | DOI:10.1038/s41598-018-27169-8; https://www.nature.com/articles/s41598-018-27169-8

Understanding 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 50 papers for 2019)

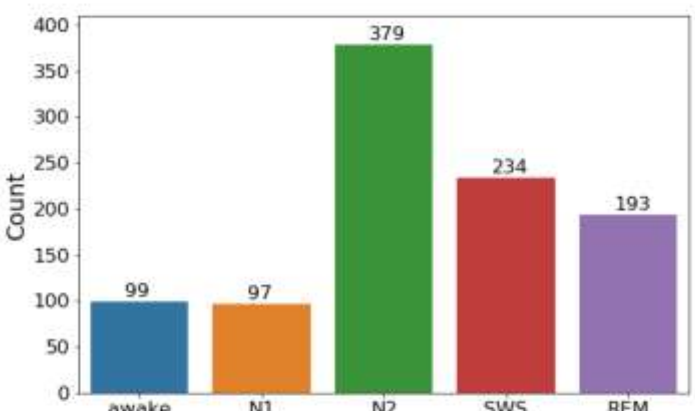


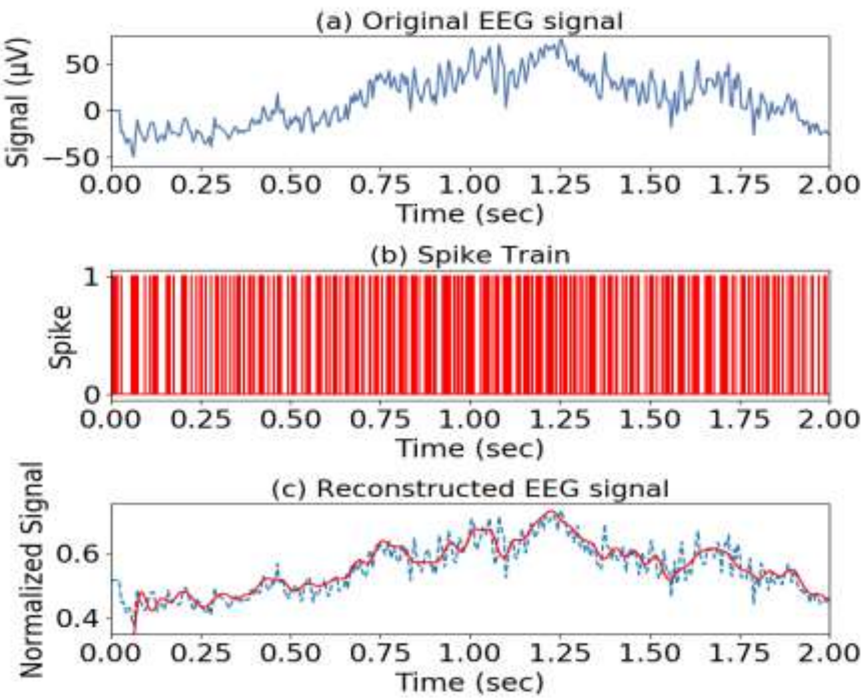
The SNN connection weights prior to MT (T1) and after following 6 weeks of training (T2) in:
(**a**) ND group,
(**b**) D+ group and
(**c**) D− group

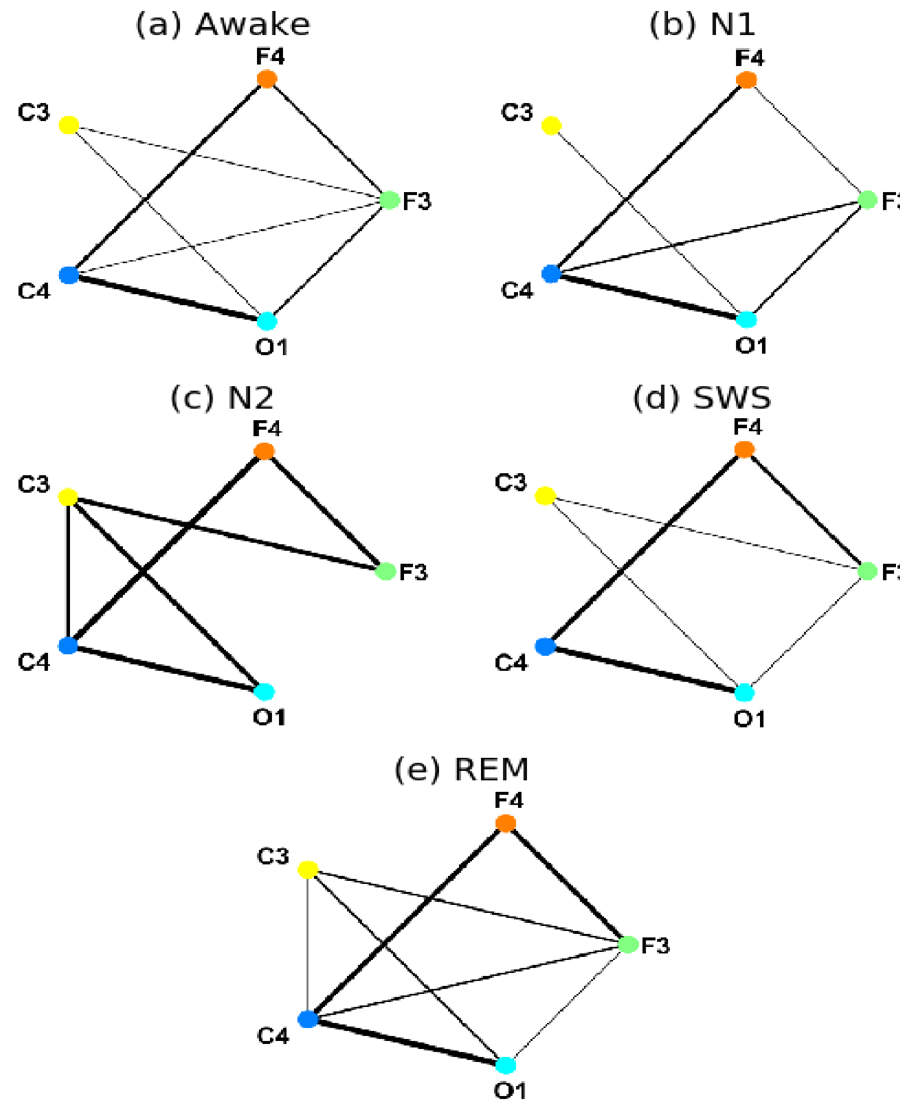
at Frontal, Temporal, Frontocentral, Centroparietal and Occipitoparietal clusters. Blue line represents the connectivity values in the SNN model at T1 (before MT) and green – at T2 (after MT).

Sleep Stage Classification EEG and using NeuCube on SpiNNaker:

S. Budhraja, B. Sen Bhattacharya, S. Durrant, Z.Doborjeh, M. Doborjeh and Nikola Kasabov, Sleep Stage Classification using NeuCube on SpiNNaker: a Preliminary Study, IEEE Proc. IJCNN2020

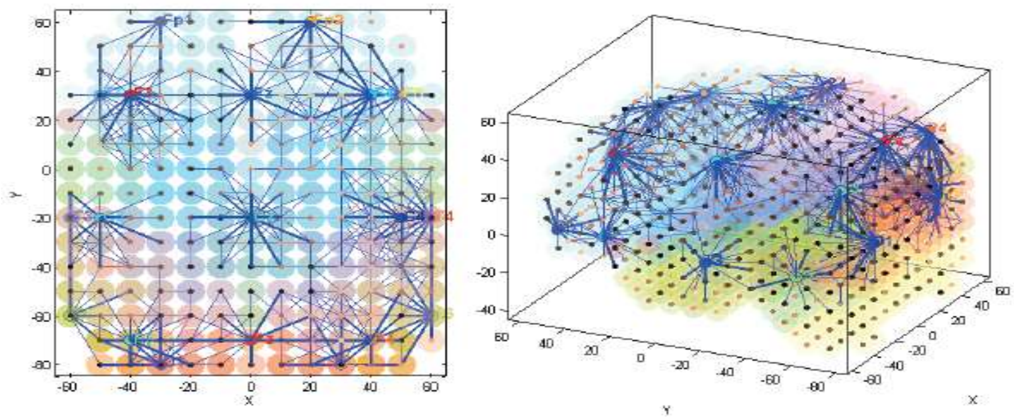




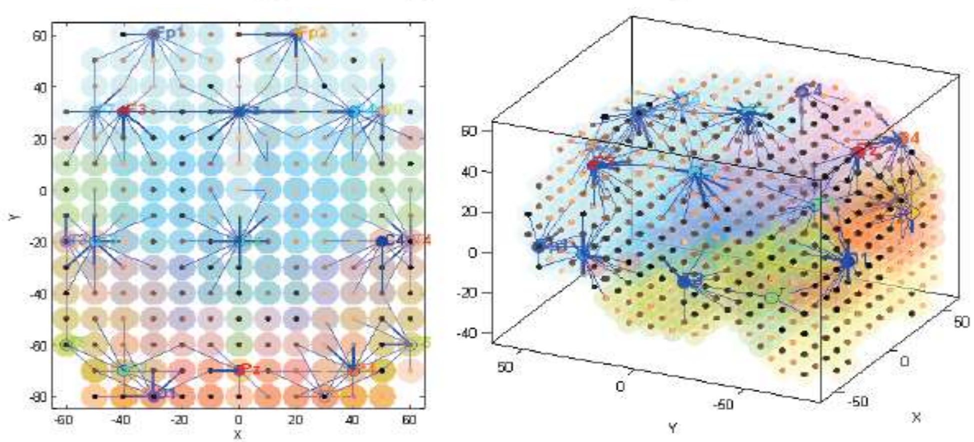


Predicting progression of MCI to AD

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.

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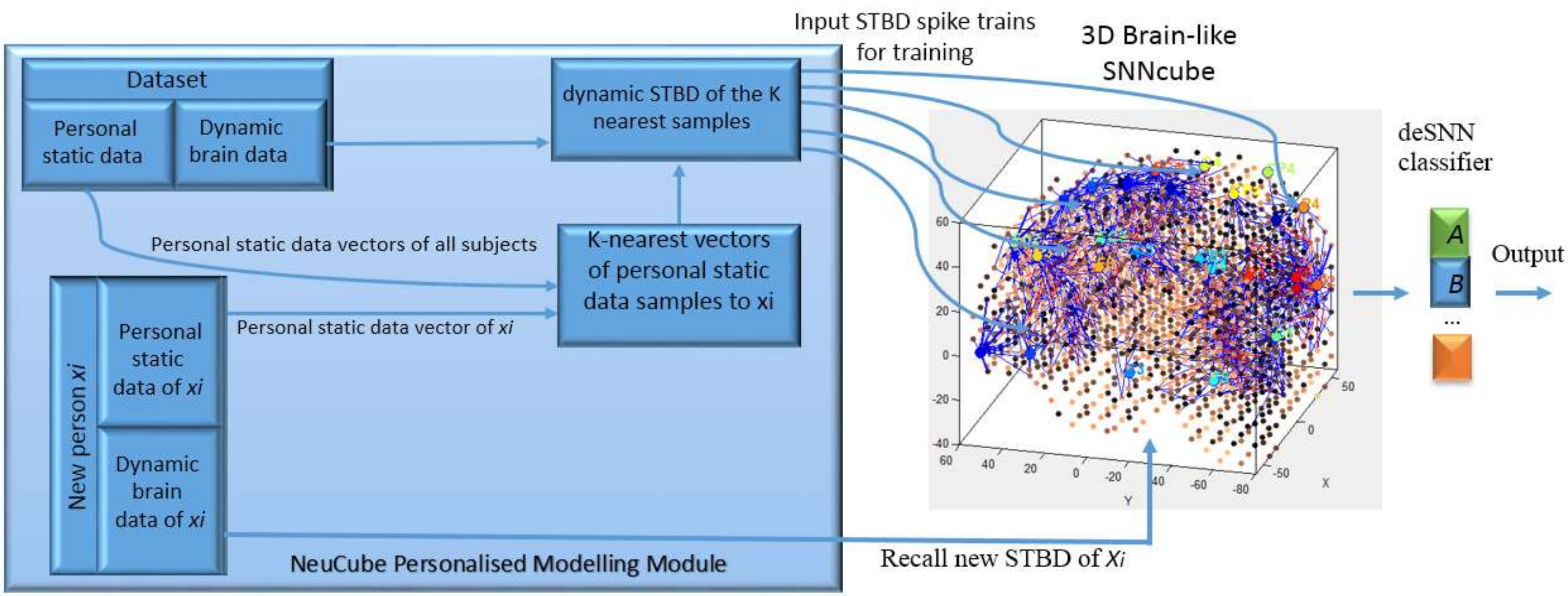
Personalised modelling for integrated static and dynamic data. Applications in neuroinformatics.

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.

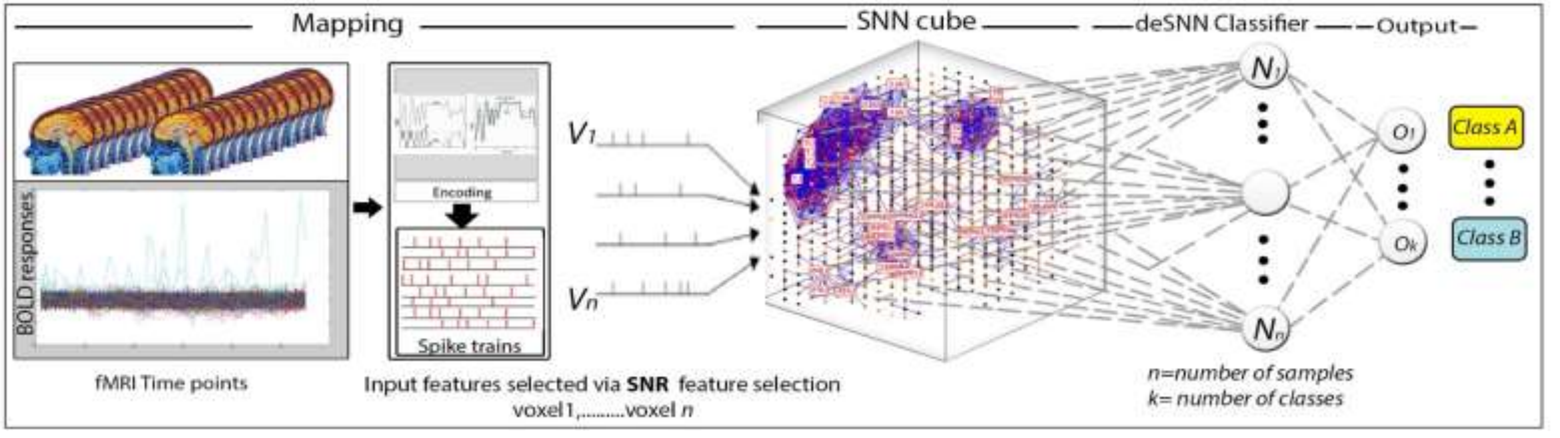


Methods	NeuCube-Personalised modelling	NeuCube- Global modelling
Classification accuracy of class M versus class OP in %	Averaged over 47 trained PSNN models: 93.61	One trained SNN model using all subjects and tested via leave-one-out method: 79.00

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)

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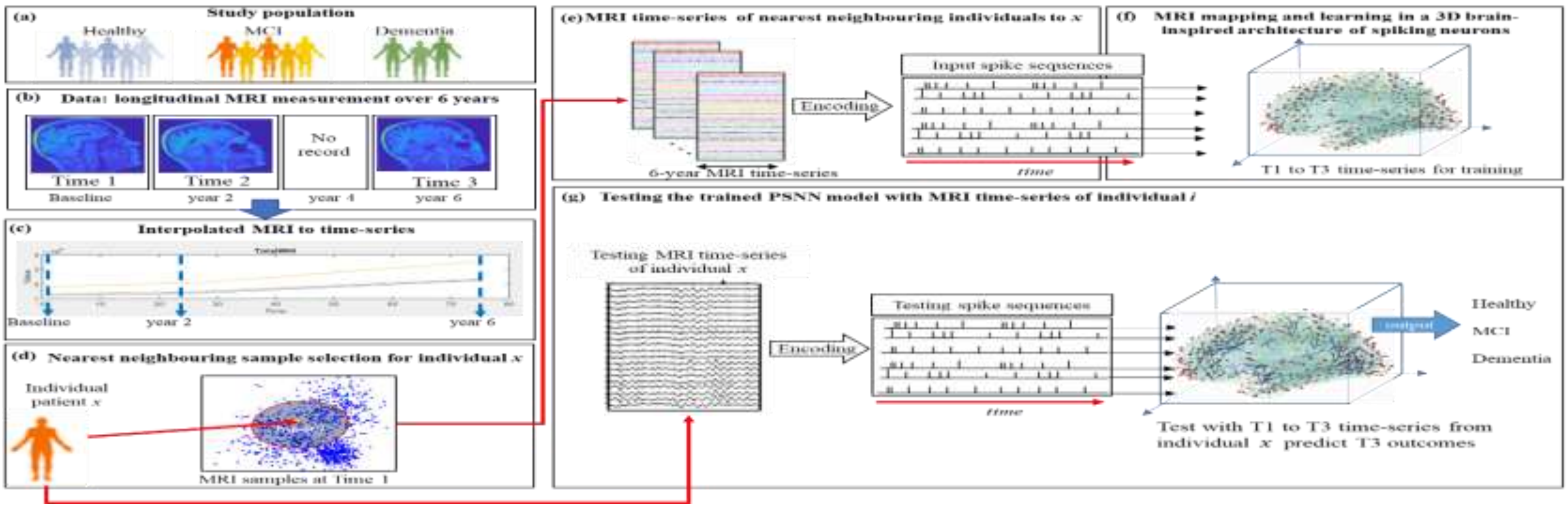
AUT

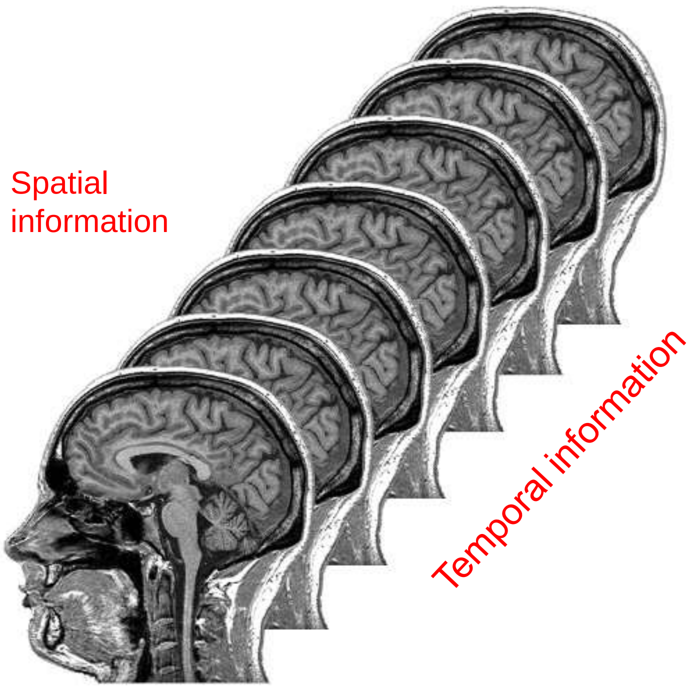
M. Doborjeh et al, Personalised Predictive Modelling with Spiking Neural Networks of Longitudinal MRI Neuroimaging Cohort and the Case Study of Dementia, Neural Networks, vol.144, Dec.2021, 522-539, https://doi.org/10.1016/j.neunet.2021.09.013,

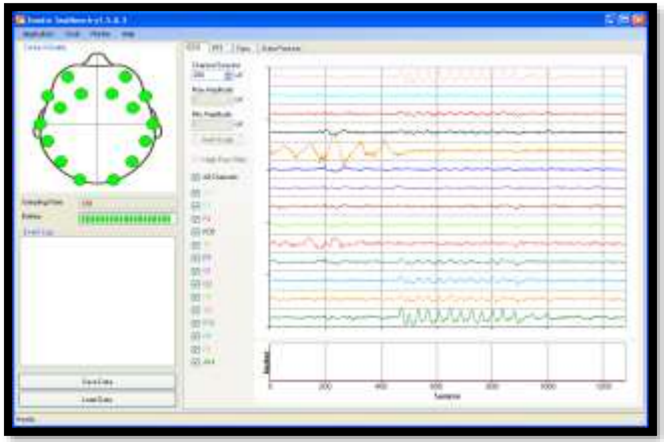


Experiment	Predict	H	MCI	D	Accuracy	Sensitivity	Specificity	Total accuracy	F-score	Parameters
Classification	H	91	0	0	97%	100%	96%	95%	94%	Learning rate: 0.02 Mod: 0.5 Drift:0.22
	MCI	3	65	1	97%	97%	97%			
	D	0	2	13	93%	98%	92%			
Two-year ahead prediction	H	88	2	0	94%	93%	97%	91%	89%	Learning rate: 0.02 Mod:0.5 Drift:0.22
	MCI	4	63	2	94%	94%	94%			
	D	2	2	12	86%	86%	97%			
Four-year ahead prediction	H	73	11	1	78%	82%	78%	73%	67%	Learning rate: 0.01 Mod:0.4 Drift:0.25
	MCI	15	46	3	69%	82%	68%			
	D	6	10	10	71%	88%	76%			
	Sum	94	67	14						

Integrating fMRI, EEG, DTI and other brain data – a challenge

Spatial
information



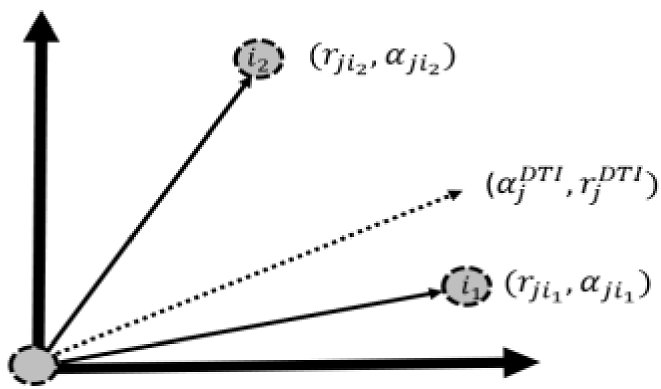


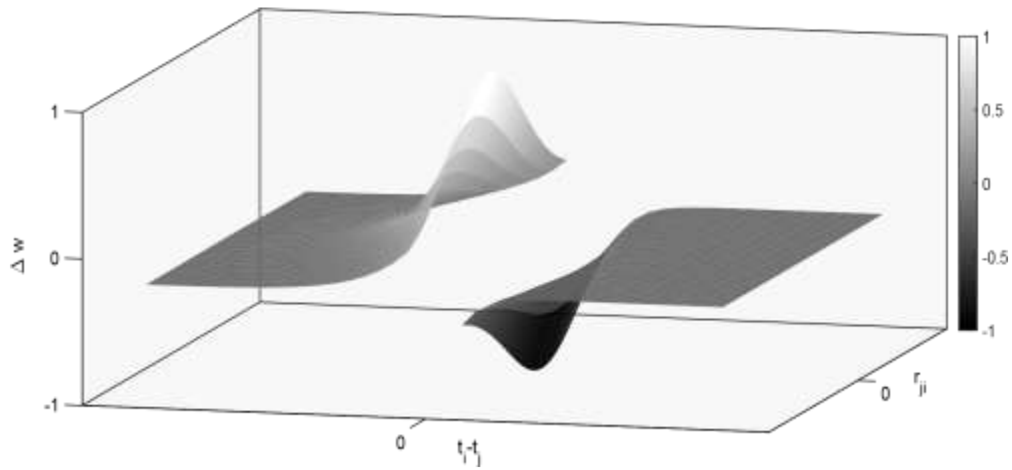
Modelling simultaneously EEG and fMRI data is an open problem:
- different time scales
- different spatial resolution

Ulster University

Integrating fMRI and DTI brain data: a new learning rule - oiSTDP

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





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

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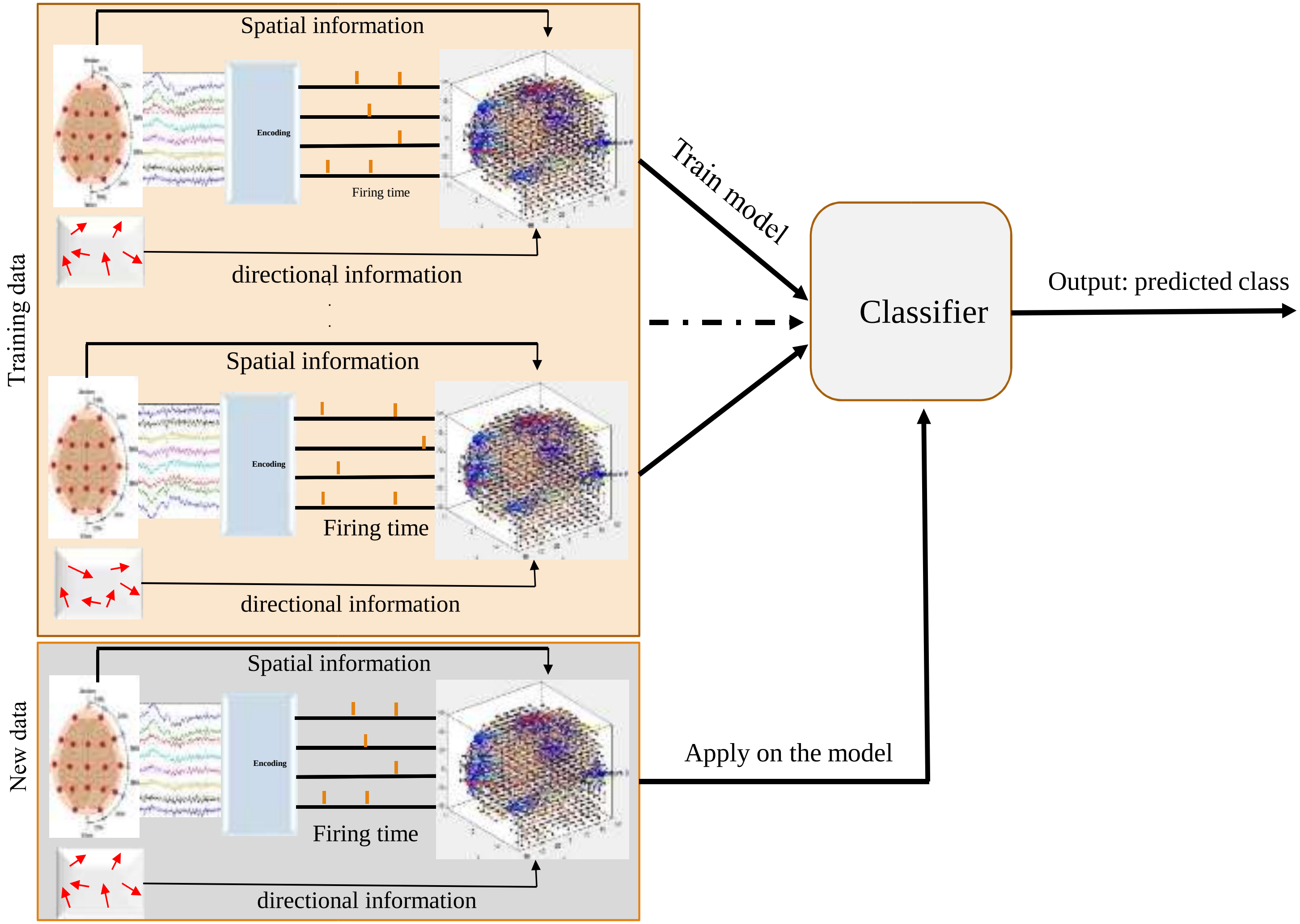
PM using both fMRI and DTI data

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

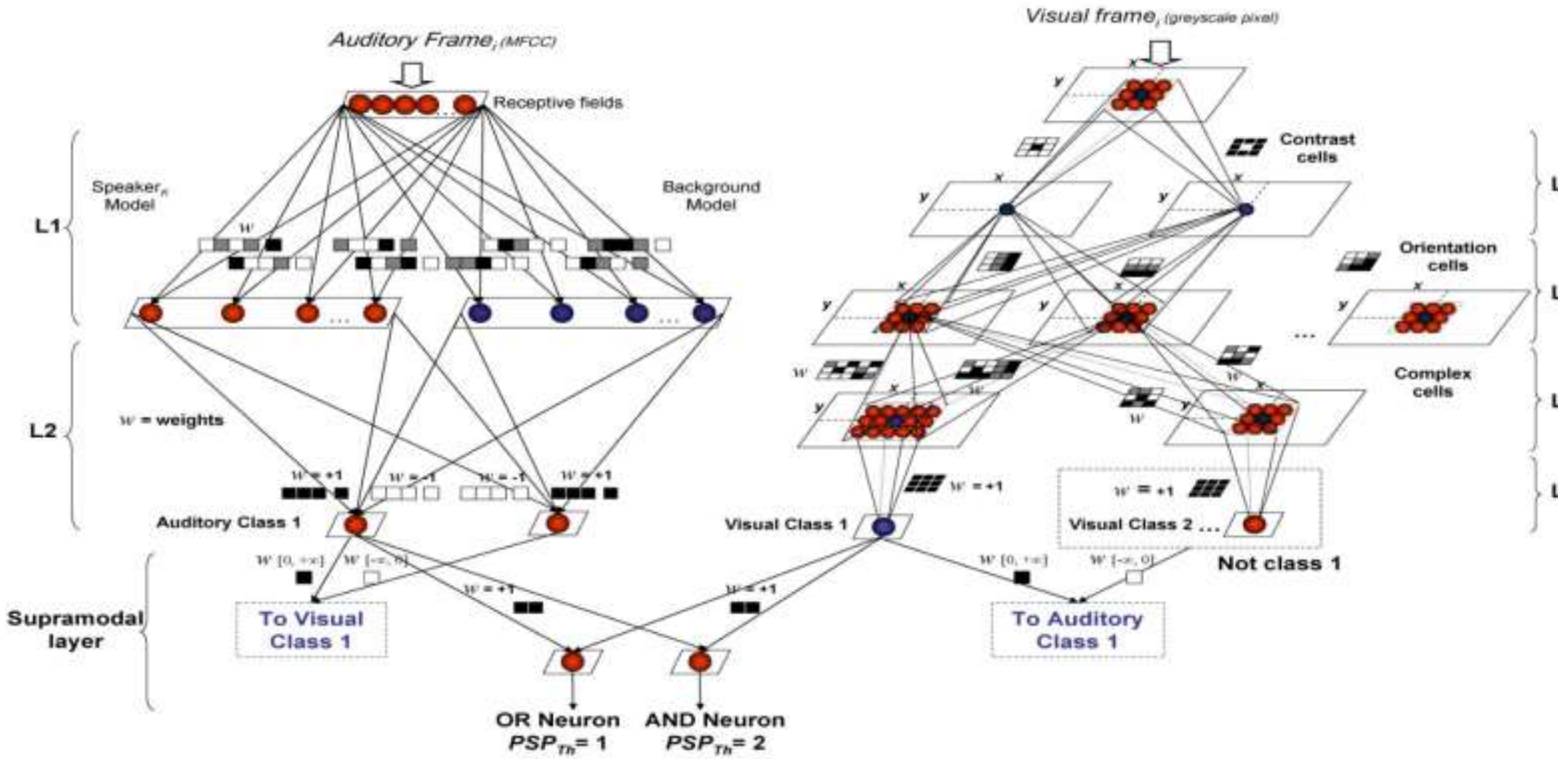


Audio- and visual information processing in the brain and its modelling with eSNN

-Convolutional layers

- Accumulation of spikes over time in the membrane potential

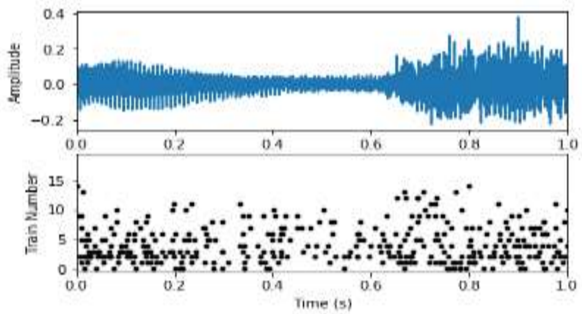
- Person authentication based on speech and face data

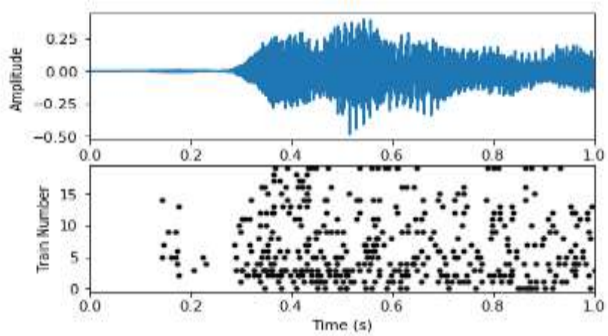


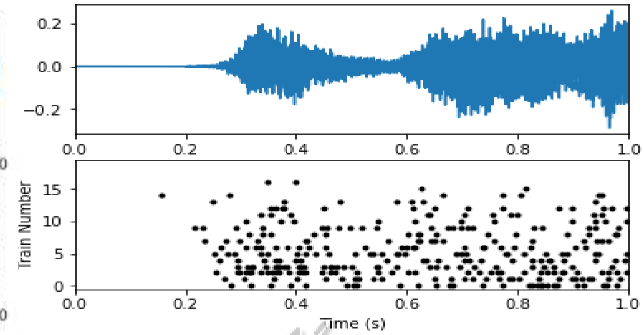
(Wysoski, S., L.Benuskova, N.Kasabov, Evolving Spiking Neural Networks for Audio-Visual Information Processing, Neural Networks, 23, 7, 819-835, 2013).

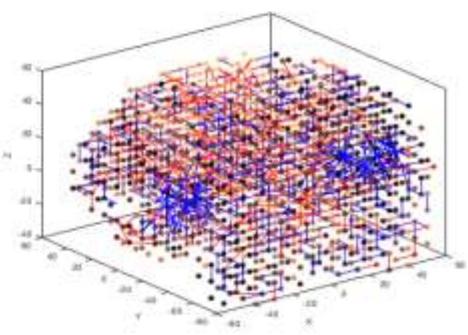
Deep learning and modelling of audio and visual and multimodal audio-visual data in BI-SNN

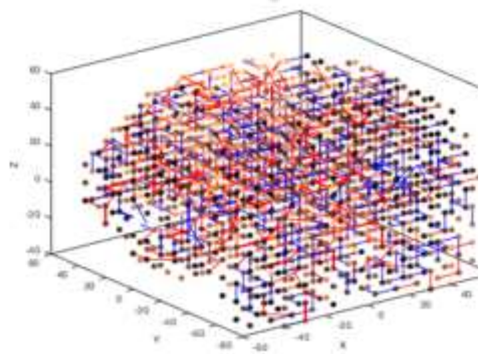
Using tonotopic, *stereo* mapping of sound and deep learning in NeuCube

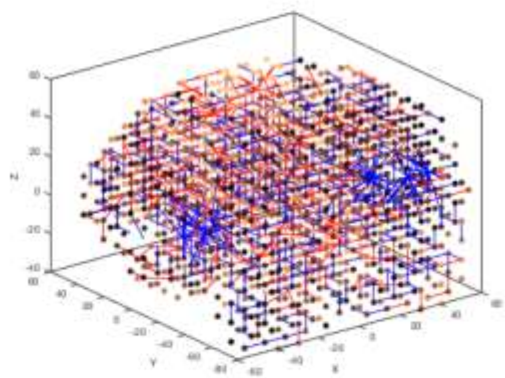






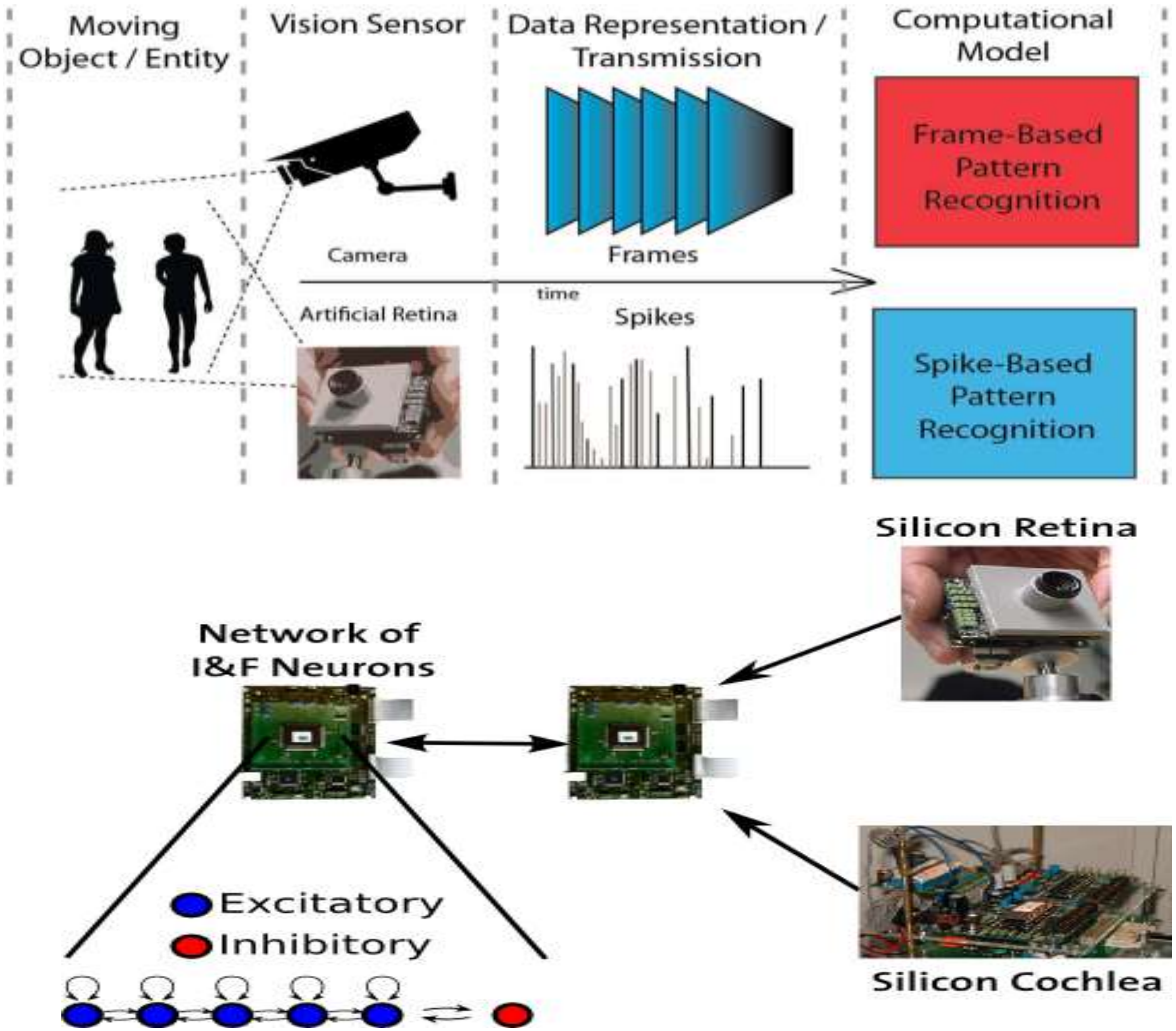






	Mozart	Bach	Vivaldi
Predicted 1	171	3	1
Predicted 2	9	176	1
Predicted 3	0	1	178

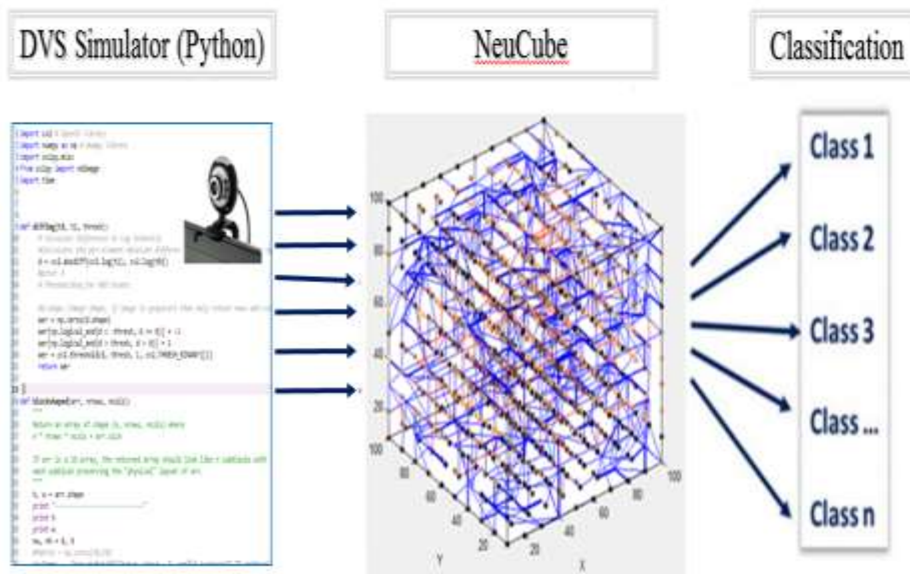
Deep learning of visual information



BI-SNN for fast object recognition from video streaming data

Applications:

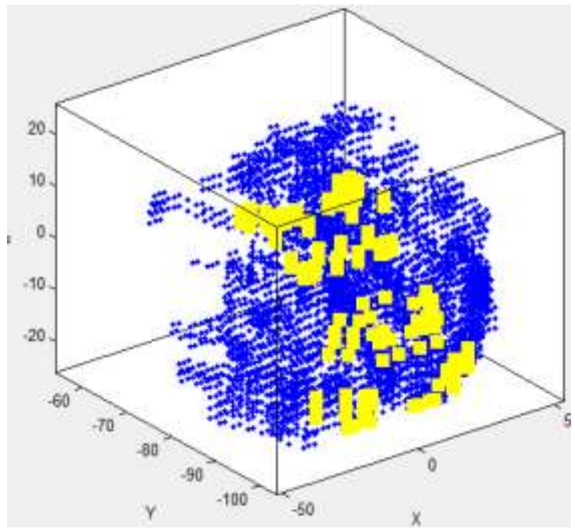
- Surveillance systems
- Cybersecurity
- Military applications
- Autonomous vehicles



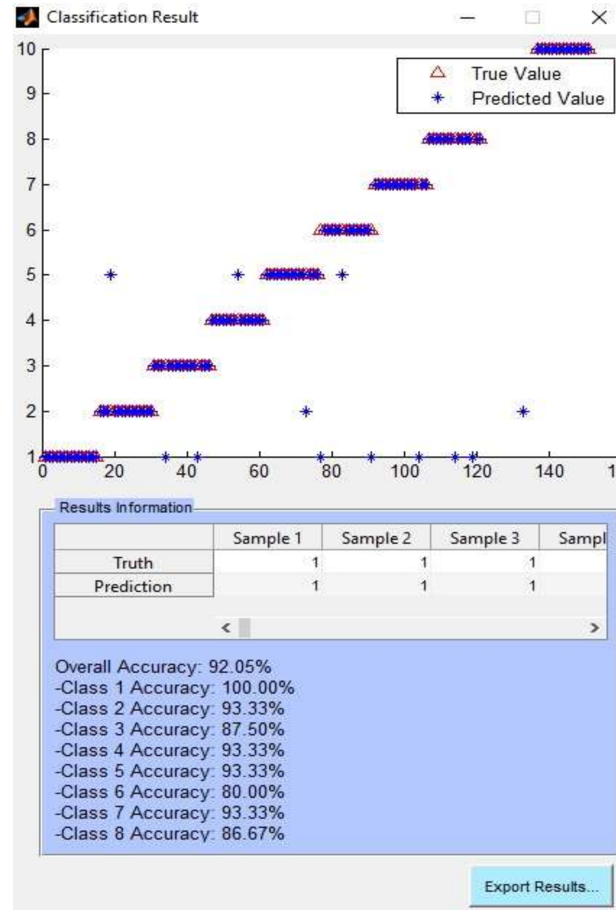
Overall Accuracy: 90.00%
-Class 1 Accuracy: 100.00%
-Class 2 Accuracy: 100.00%
-Class 3 Accuracy: 80.00%
-Class 4 Accuracy: 80.00%

Moving object recognition using retinotopic mapping and TL in NeuCube and DVS spike encoding

30000 moving digits in 8 fonts and sizes



NeuCube with 4262 neurons from V1 and V2

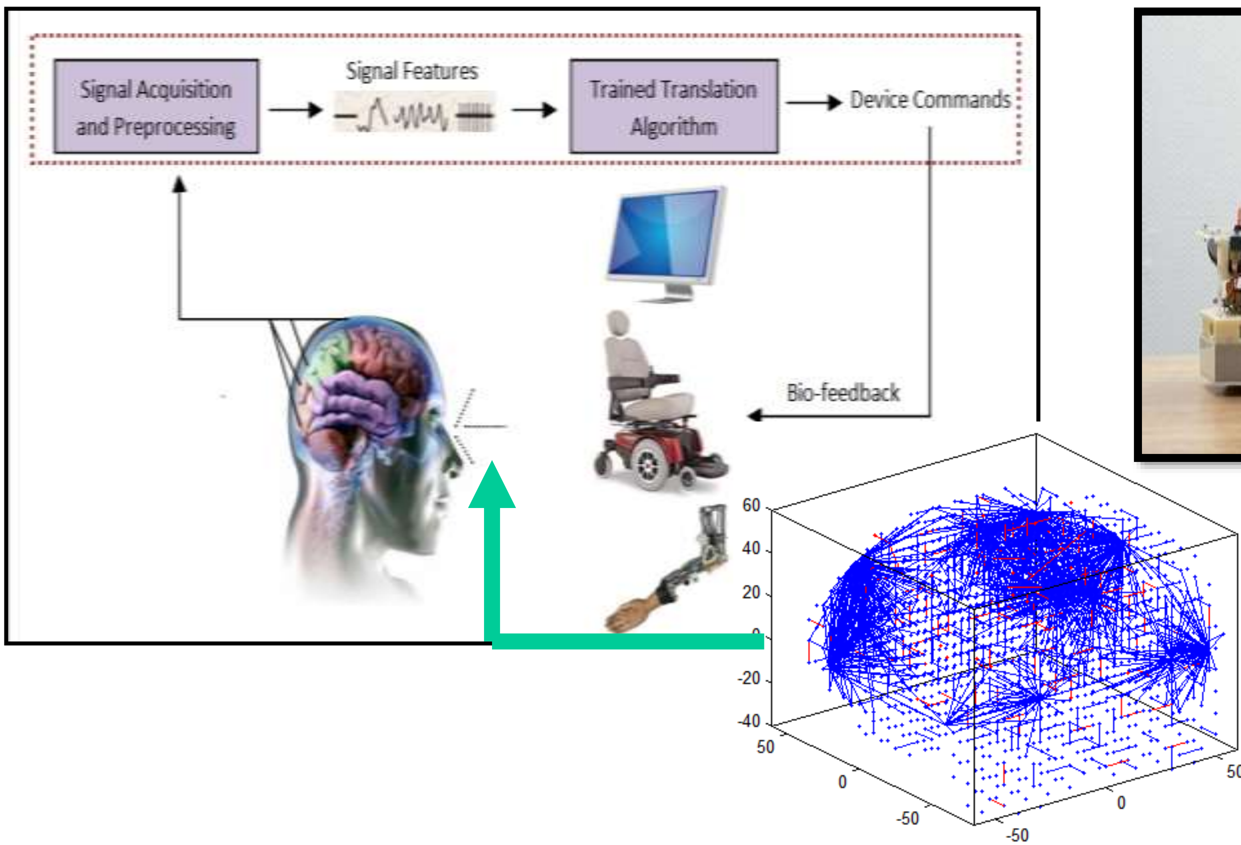


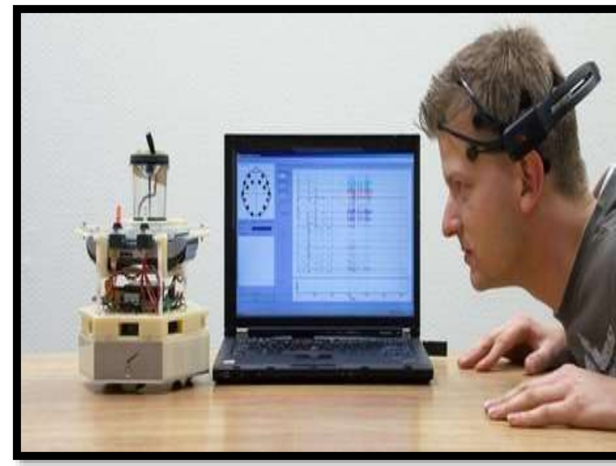
L.Paulin, A.Abbott, N.Kasabov, A retinotopic spiking neural network system for accurate recognition of moving objects using NeuCube and dynamic vision sensors, Frontiers of Comp. Neuroscience, 2018.

Brain Computer 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.

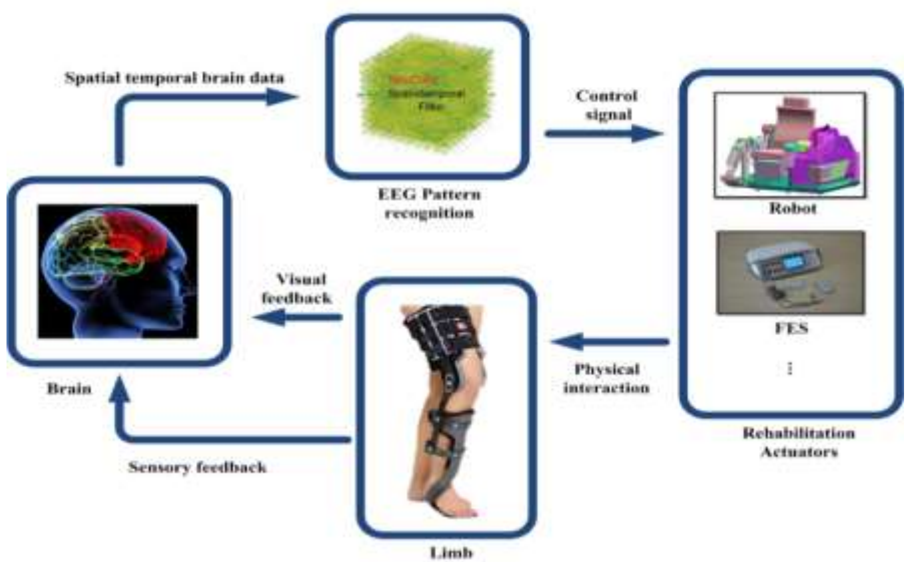


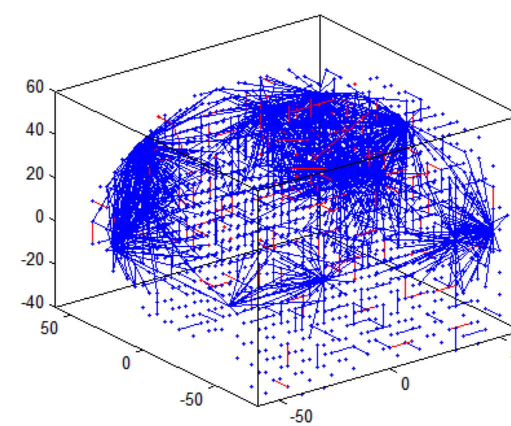


BI-SNN for neurorehabilitation

(with CASIA China, Prof. Zeng-Guang Hou)

1. D. Taylor, N.Scott, N. Kasabov, E.Capecci, E. Tu, N. Saywell, Y. Chen, J.Hu and Z.Hou, Feasibility of NeuCube SNN architecture for detecting motor execution and motor intention for use in BCI applications, Proc. WCCI 2014, Beijing, 7-13 July 2014, IEEE Press.
2. Hu, J., Hou, Z., Chen, Y., Kasabov, N., & Scott, N. (2014). EEG-Based Classification of Upper-Limb ADL Using SNN for Active Robotic Rehabilitation. In 2014 5th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (pp. 409-414). Sao Paolo, Brazil: IEEE. doi:10.1109/BIOROB.2014.6913811
3. N. Kasabov, J.Hu, Y. Chen, N.Scott, and Y. Turkova, Spatio-temporal EEG data classification in the NeuCube 3D SNN Environment: Methodology and Examples, Proc. ICONIP 2013, Springer LNCS, vol.8228, pp.63-69.
4. Y.Chen, J.Hu, N.Kasabov, Z. Hou and L.Cheng, NeuroCubeRehab: A Pilot Study for EEG Classification in Rehabilitation Practice Based on Spiking Neural Networks, Proc. ICONIP 2013, Springer LNCS, vol.8228, pp.70-77.





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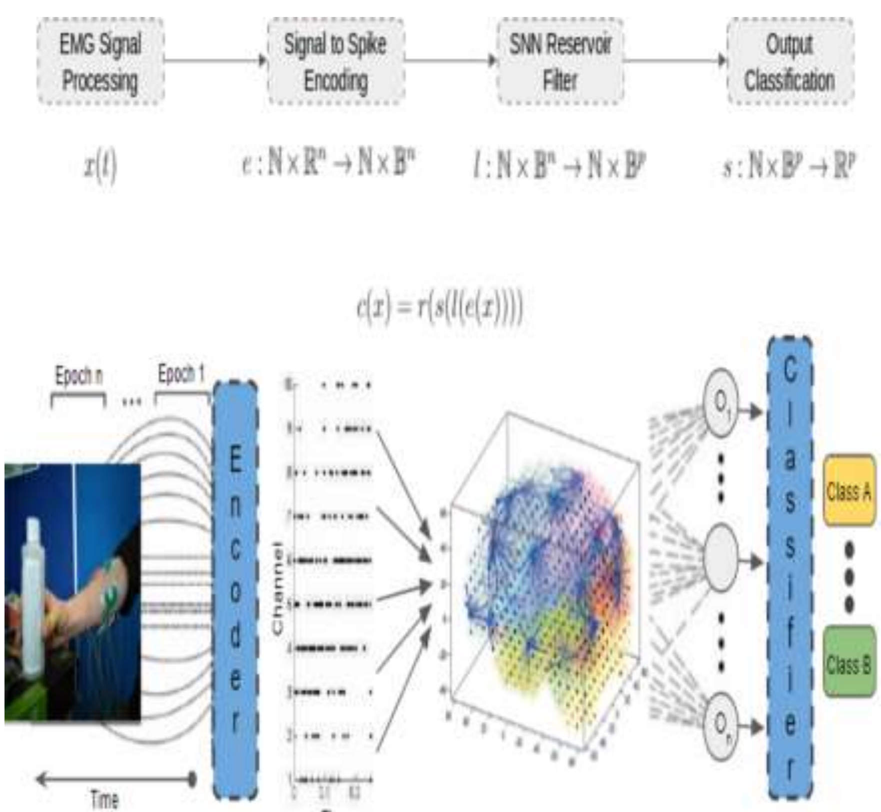
Deep learning and classification of spatio-temporal EMG signals for neurorehabilitation control using NeuCube implemented on SpiNNaker

J.Behrenbeck, Z.Tayeb, C.Bhiri, C.Richter, O.Rhodes, N.Kasabov, S.Furber, G.Cheng, J.Conradt, Classification and Regression of Spatio-Temporal EMG Signals using NeuCube Spiking Neural Network and its implementation on SpiNNaker Neuromorphic Hardware", Journal of Neural Engineering, IOP Press, vol.16, No.2 2019, https://iopscience.iop.org/article/10.1088/1741-2552/aafabc



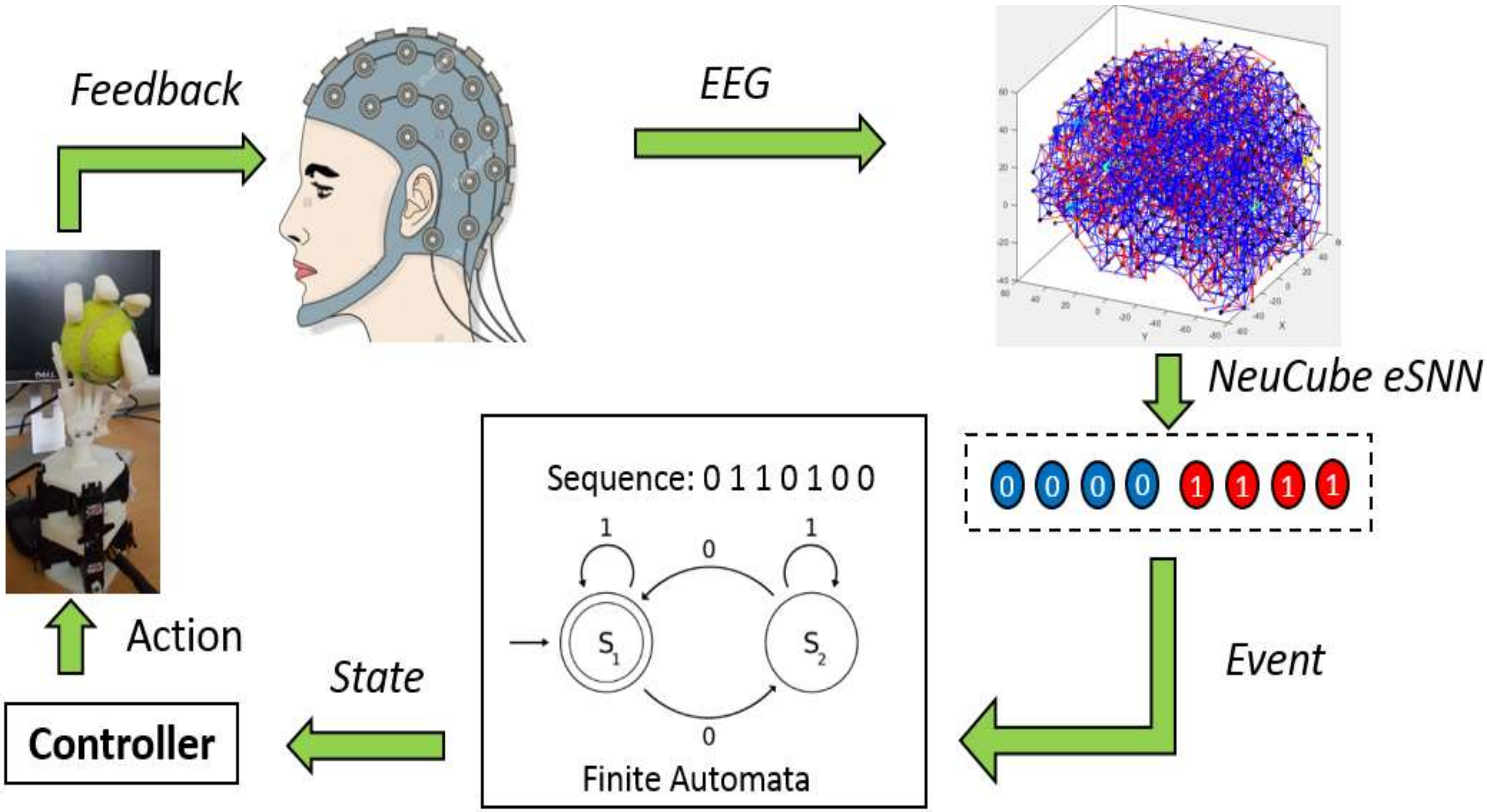
The work investigates the use of the NeuCube spiking model to directly classify different grasp movements from raw EMG data as well as the estimation of the applied finger forces.

A better classification accuracy using the NeuCube model compared to traditional machine learning methods, i.e. validation accuracy of 85.5%, a test accuracy of 81% as well as less than 2% of root mean square error (RMSE) when estimating finger forces, using EMG data collected from four different human subjects.

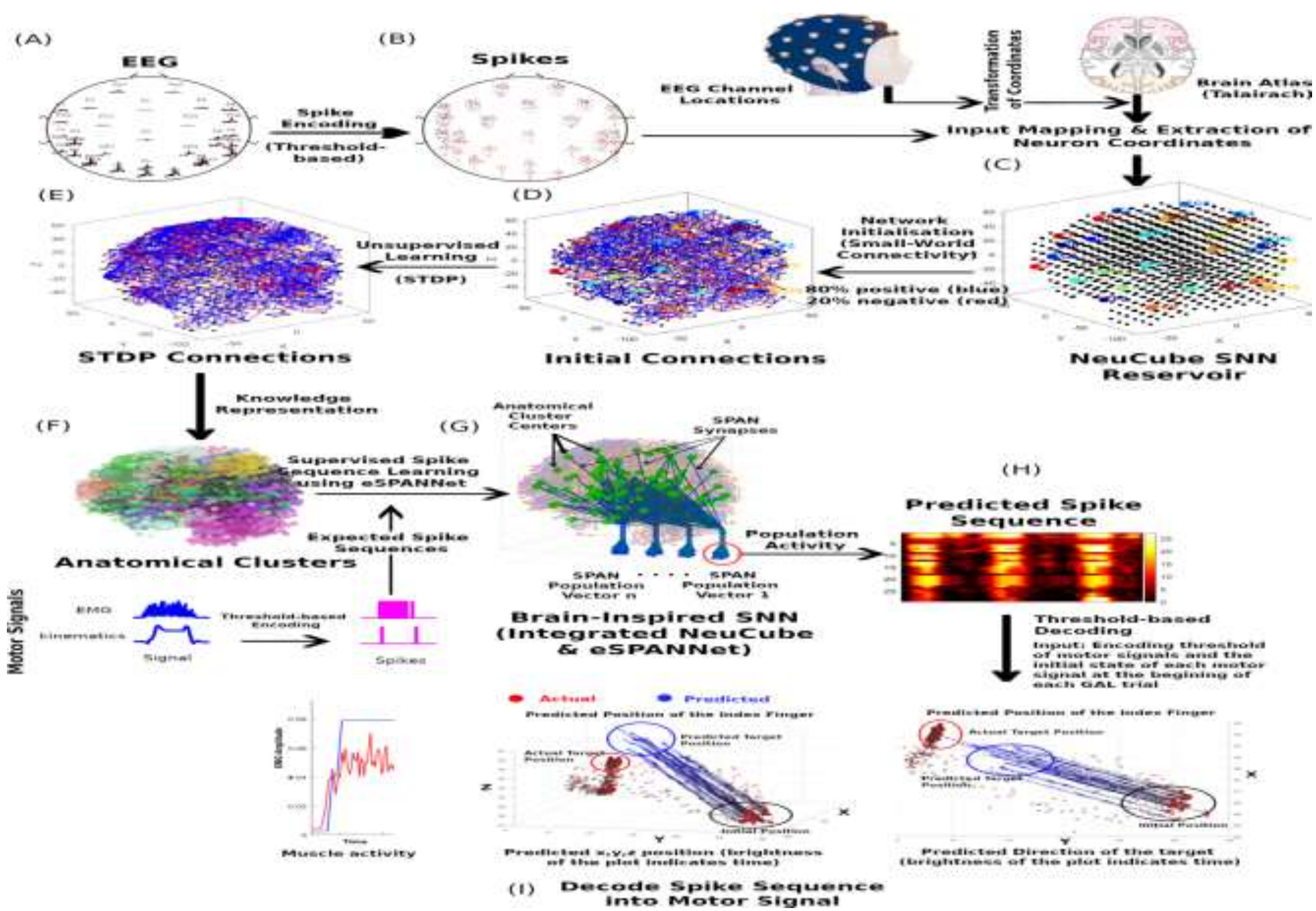
This approach can be further investigated to achieve a smooth, accurate and adaptive control of prosthetics for complex movements within a larger time window.

FaNeuRobot: A Brain-Like Motor Controlling Framework for Prosthetic Control using Automata Theory, Cognitive Computing & NeuCube

K. Kumarasinghe, M. Owen, N. Kasabov, D. Taylor, Chi Kit Au, Proc. IEEE Robotics Conference, Sydney, May 2018.



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



Integration of the eSPANNet with the NeuCube SNN architecture and major steps in training a BI-SNN model—(**A**) filtered EEG, (**B**) spike encoding, (**C**) extraction of brain coordinates from a brain template and mapping EEG channel locations, (**D**) initialisation of the SNN based on the small-world connectivity principle, (**E**) unsupervised spike time dependent plasticity learning, (**F**) extraction of anatomical clusters, (**G**) training population vectors using eSPANNet learning, (**H**) predicted spike sequence by the SNN, (**I**) decoding predicted spike sequences into muscle activity and kinematics using the threshold-based decoding.

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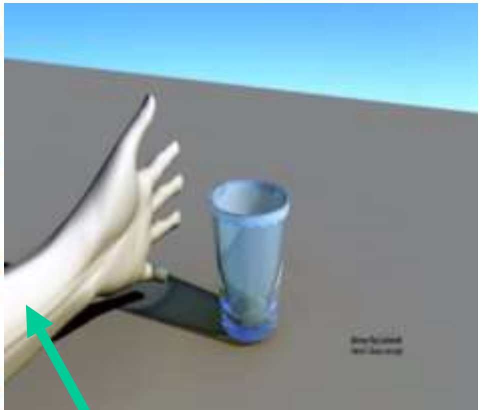
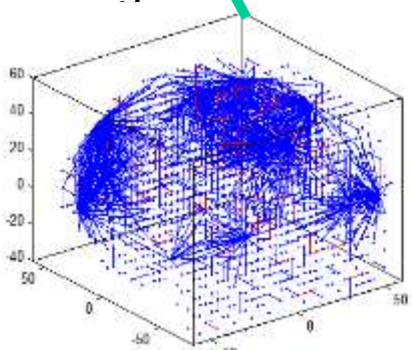
Learning and understanding brain-computer (VR/AR) interaction in time-space

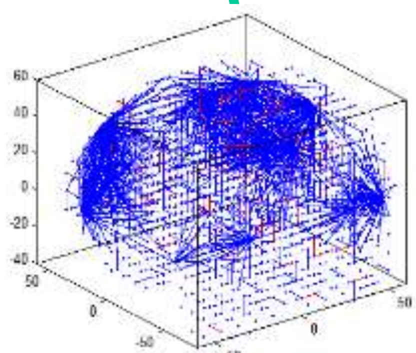


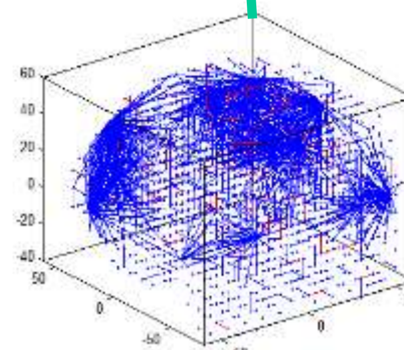
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.

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.



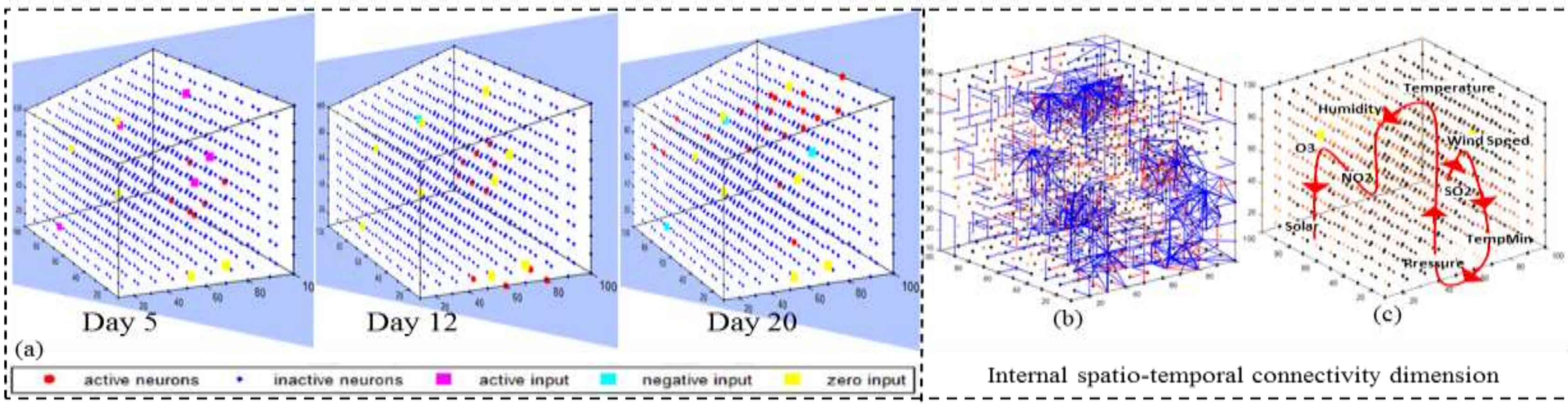




Deep learning of multisensory streaming data

Kasabov, N., Feigin, V., Hou, Z. -G., Chen, Y., Liang, L., Krishnamurthi, R., Parmar, P. (2014). Evolving spiking neural networks for personalised modelling, classification and prediction of spatio-temporal patterns with a case study on stroke. Neurocomputing, 134, 269-279. doi:10.1016/j.neucom.2013.09.049

Three snapshots of a NeuCube model during training on temporal climate and air pollution data of 9 variables, measured on each of 20 days before a stroke event happened to patients from a selected group (the left 3 figures). The evolved connectivity in the 3D SNN model after training – spatio-temporal structural patterns of connections are learned in the 3D dimensionality of the model. A dynamic functional pattern learned in the functional space of climate variable changes (the right most figure).

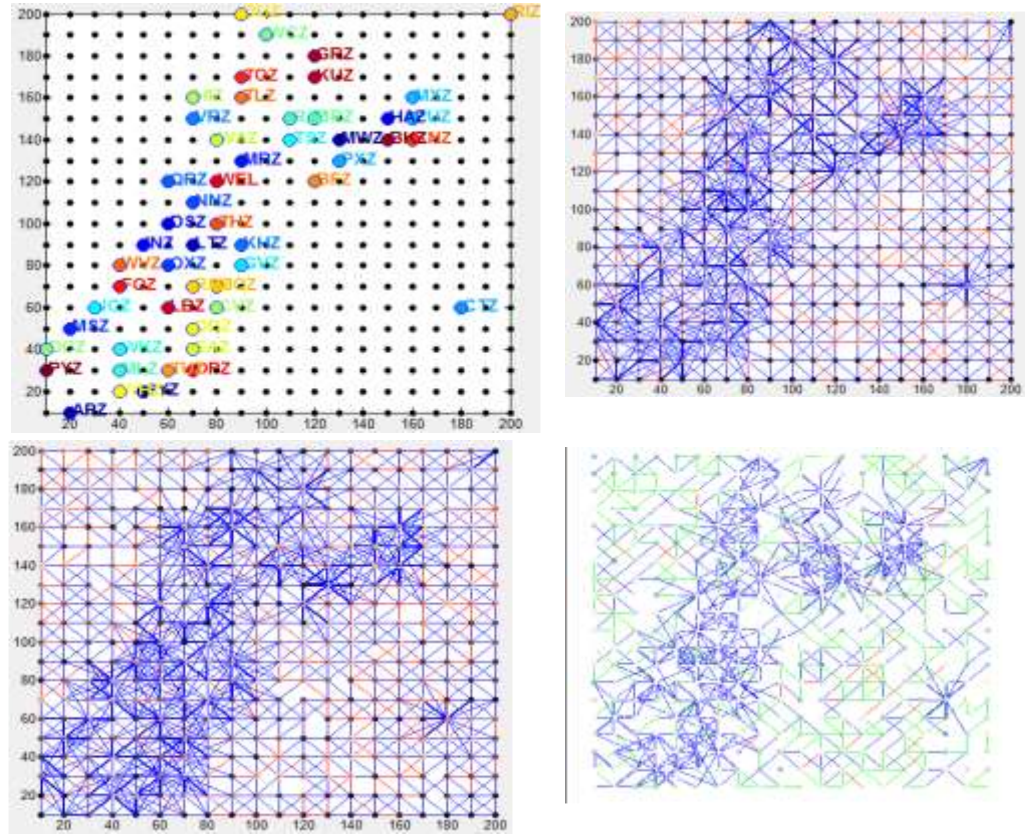


A spatio-temporal rule extracted from a trained SNNcube on climate data relate to a high risk of stroke for a group of individuals

IF SO2 changes around time T1) AND (Wind Speed changes around time T2)
AND (TempMin changes around time T3) AND (Pressure changes around time T4)
AND (AvTemp changes around time T5) AND (Humidity changes around time T6)
AND (NO2 changes around time T7) AND (O3 changes around time T8) AND (Solar eruption around T9)
THEN (High risk of stroke for the individual X and the group she/he belongs to)

Seismic spatio-temporal data modelling for earthquake prediction

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.



Measure	NeuCube	SVM	MLP	1h
ahead	**91.36%**	65%	60%	
6h ahead	**83%**	53%	47%	
12h ahead	**75%**	43%	46%	

Predicting risk for earthquakes, tsunami, land slides, floods – how early and how accurate?

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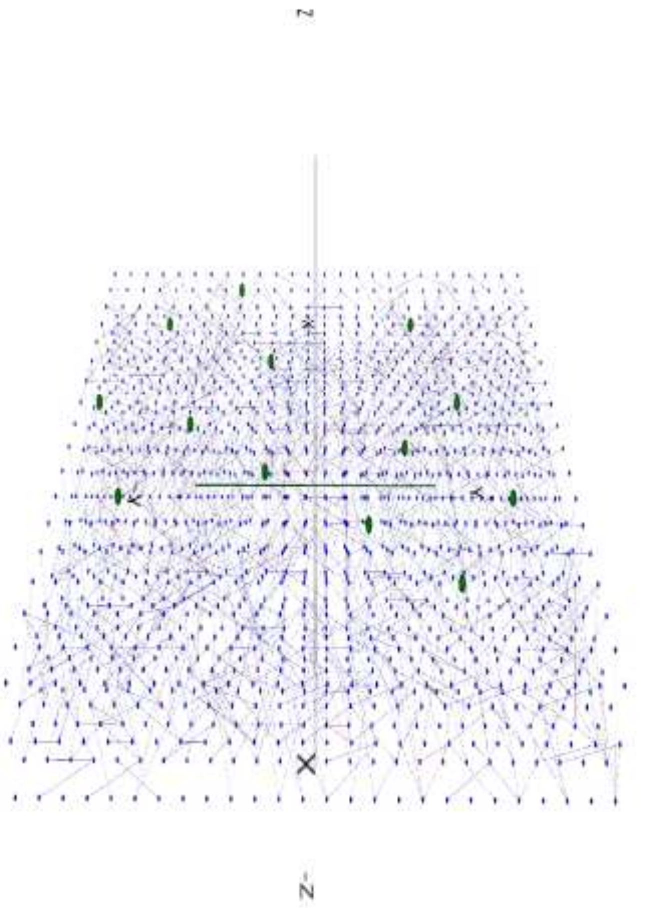
Wind speed, location and direction modelling for energy prediction from wind turbines

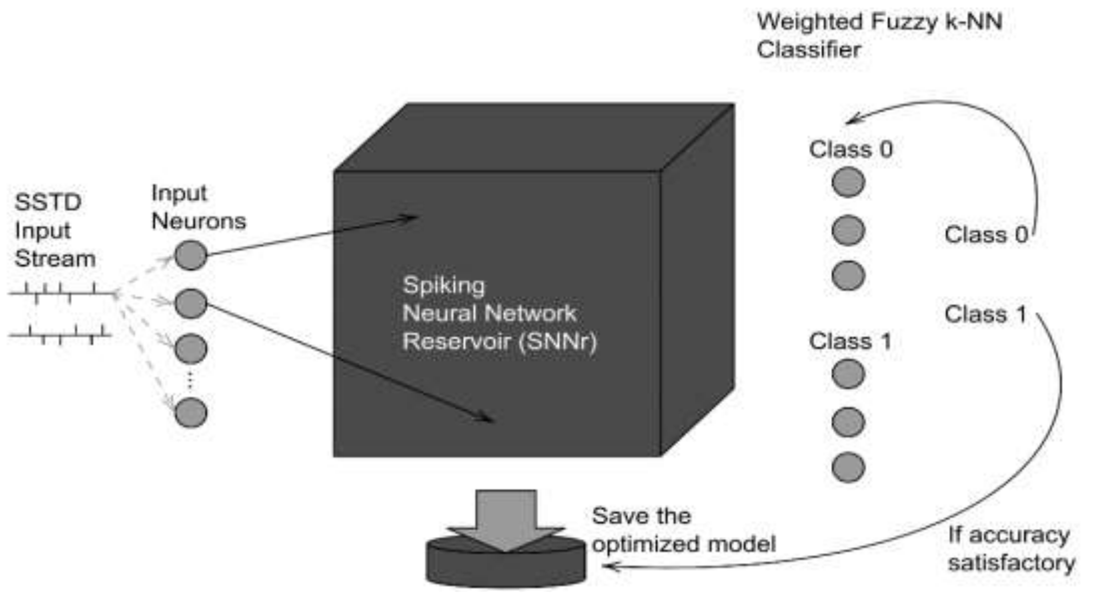
New Zealand

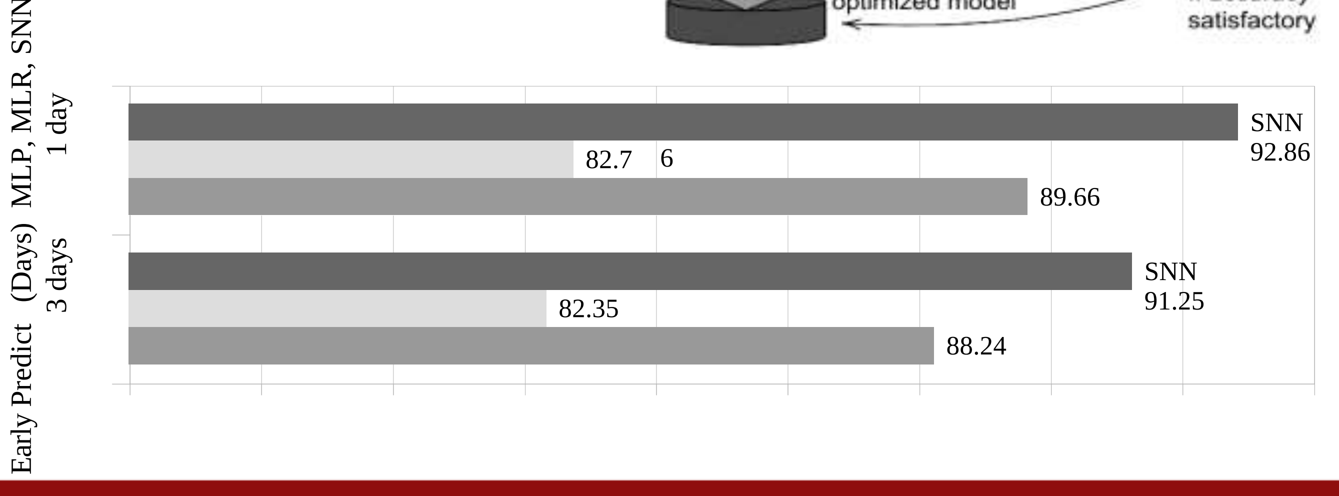


Xinjiang, China (中国新疆)

Flood events risk assessment using environmental spatio-temporal data

Mohd Hafizul Afifi Abdullah, **Muhaini Othman**, Shahreen Kasim, Siti Aisyah Mohamed, Evolving spiking neural networks methods for classification problem: a case study in flood events risk assessment, Indonesian Journal of Electrical Engineering and Computer Science Vol. 16, No. 1, October 2019, pp. 222~229 ISSN: 2502-4752, DOI: 10.11591/ijeecs.v16.i1.pp222-229, *http://iaescore.com/journals/index.php/ijeecs*





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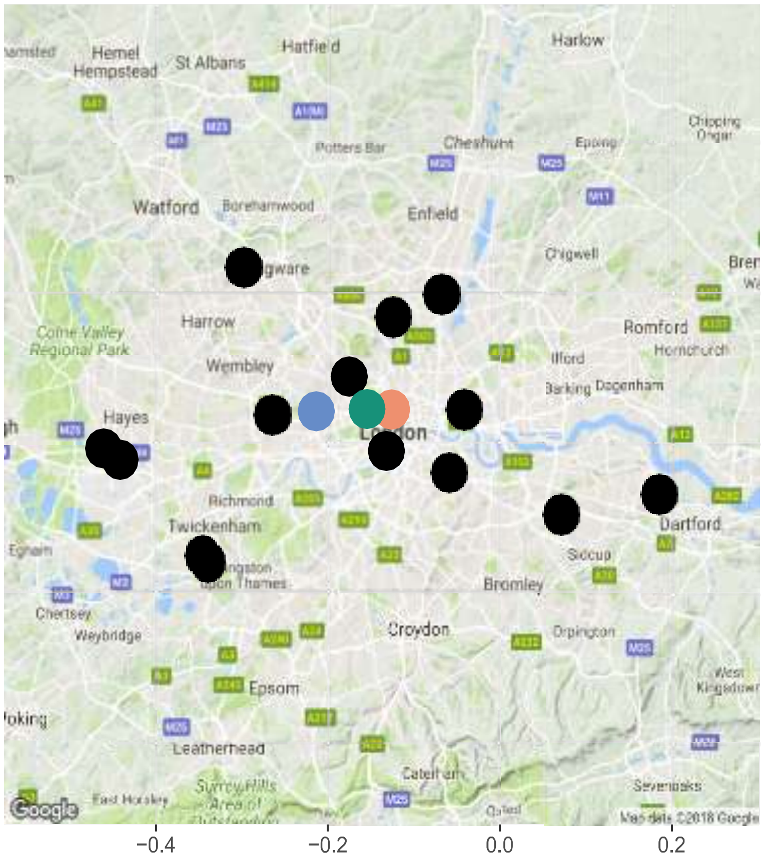
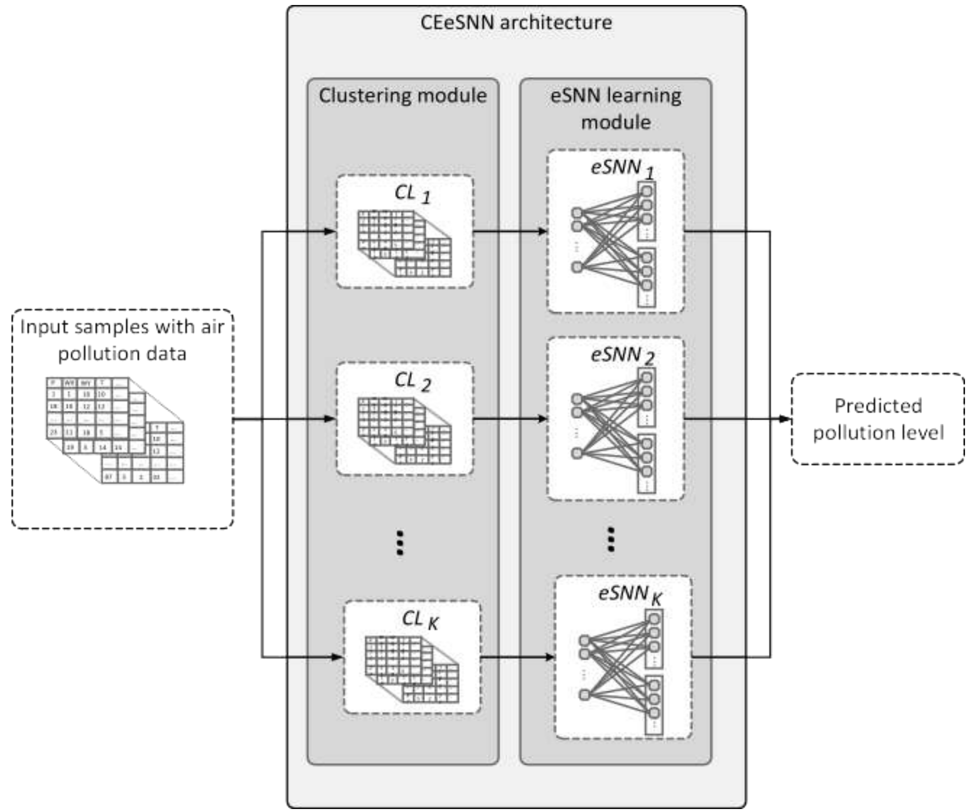
Using an ensemble of eSNN for Predicting Hourly Air Pollution in London Area from sensory TSD

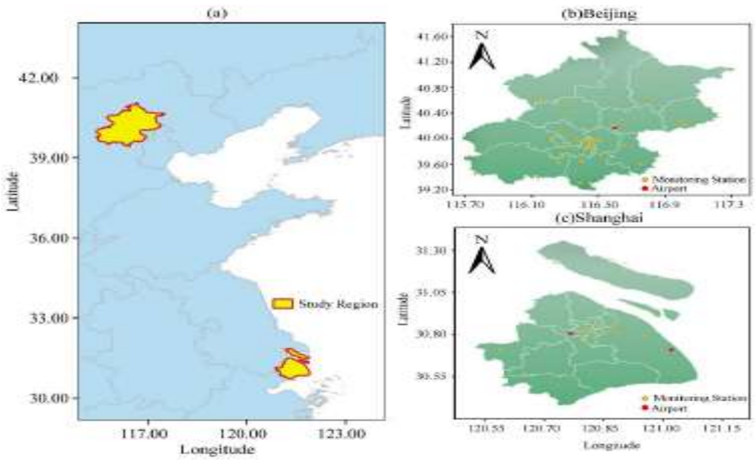


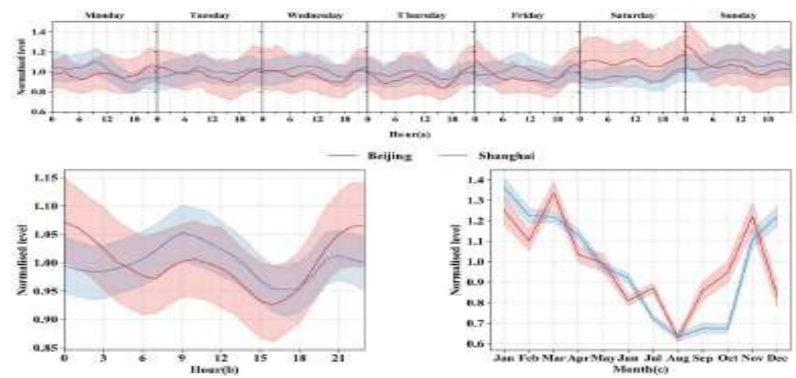


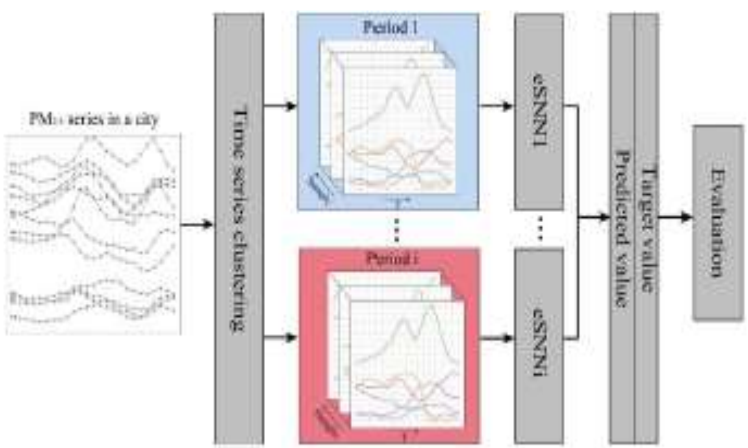
P. S. P Maciaga, N. K. Kasabov, M. Kryszkiewicza, R. Benbenik, Prediction of Hourly Air Pollution in London Area Using Evolving Spiking Neural Networks, Environmental Modelling and Software, Elsevier, vol.118, 262-280, 2019, https://www.sciencedirect.com/science/article/pii/S1364815218307448?dgcid=author

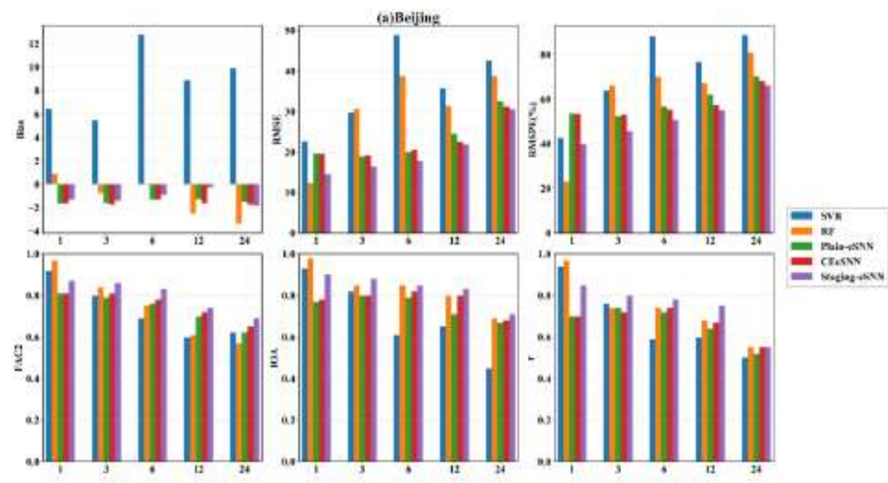
Evolving Spiking Neural Network Model for PM2.5 Hourly Concentration Prediction Based on Seasonal Differences: A Case Study on Data from Beijing and Shanghai

Hengyuan Liu, Guibin Lu,Yangjun Wang, Nikola Kasabov, Evolving spiking neural network model for PM2.5 hourly concentration prediction based on seasonal differences: A case study on data from Beijing and Shanghai, Aerosol and Air Quality Research, vol.21, Issue 2, Feb. 2021, 200247, https://doi.org/10.4209/aaqr.2020.05.0247









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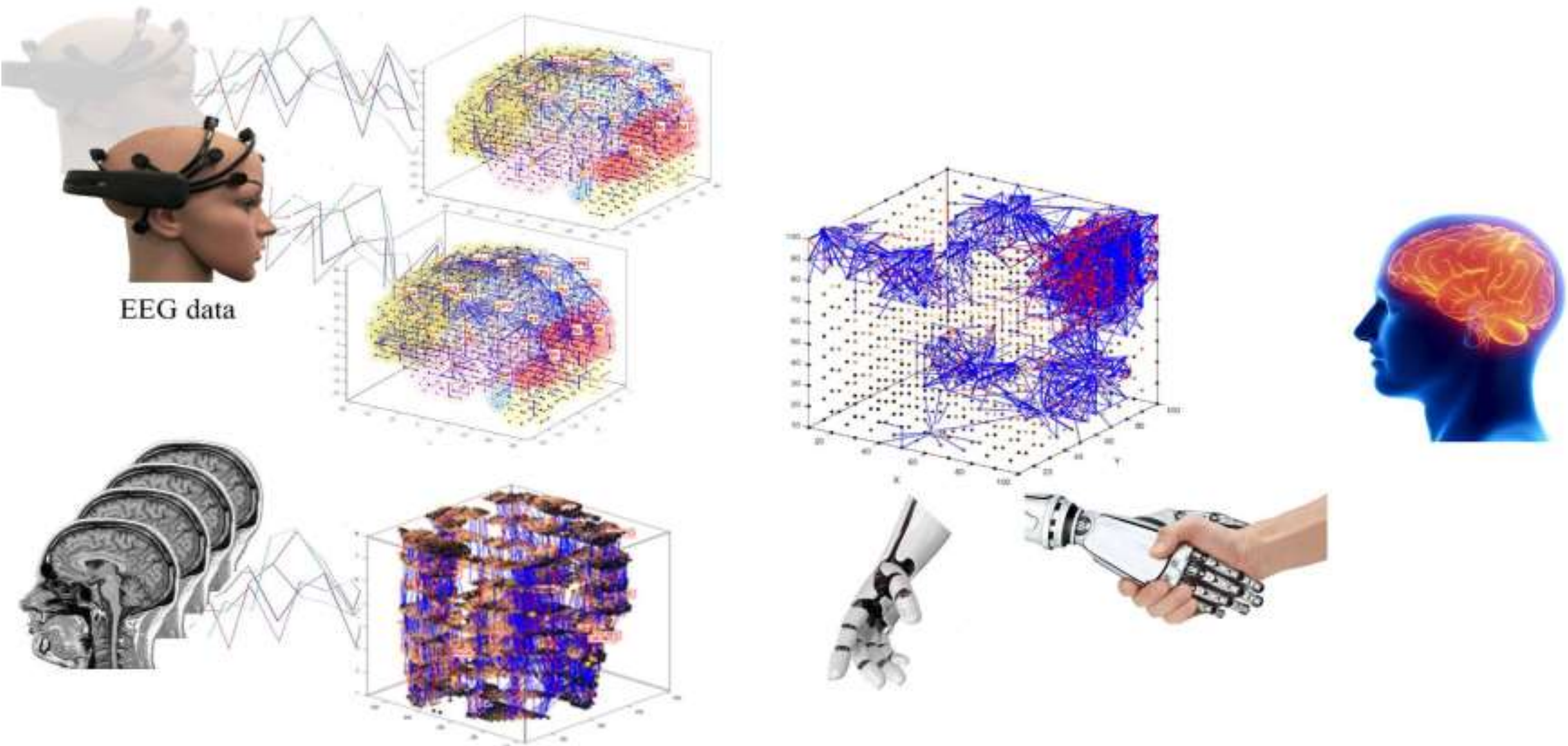
6. Conclusion and further direction

Towards a Symbiosis of Human Intelligence and AI through BI-SNN

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)



Studies on hyper-scanning

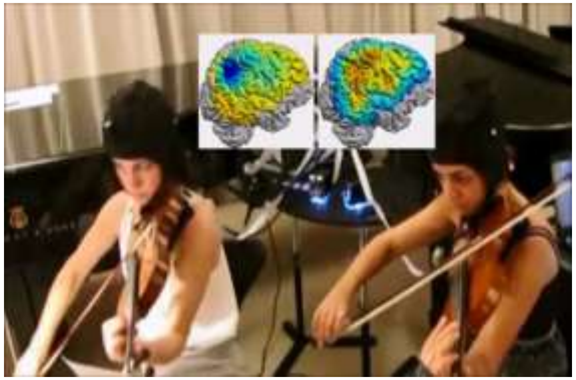
- Social neuroscience and hyperscanning techniques: Past, present and future, FabioBabiloni, LauraAstolfi, https://doi.org/10.1016/j.neubiorev.2012.07.006

- Front Psychol. 2018; 9: 1862, Published online 2018 Oct 8, doi: 10.3389/fpsyg.2018.01862, Interactive Brain Activity: Review and Progress on EEG-Based Hyperscanning in Social Interactions
- Difei Liu, Shen Liu, Xiaoming Liu, Chong Zhang, Aosika Li, Chenggong Jin, Yijun Chen, Hangwei Wang, and Xiaochu Zhang

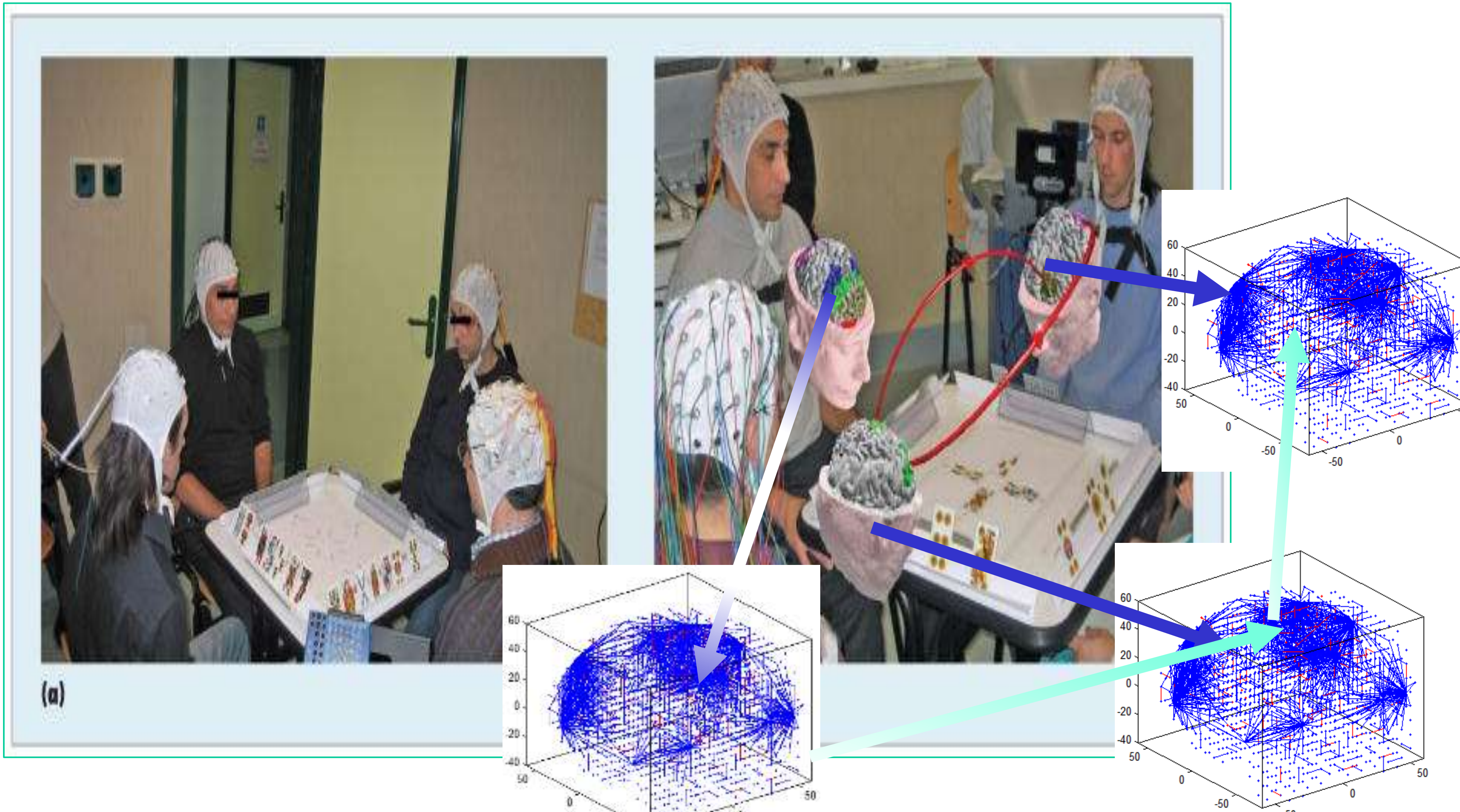
- http://qims.amegroups.com/article/view/21624/21139, Concurrent mapping of brain activation from multiple subjects during social interaction by hyperscanning: a mini-review, Meng-Yun Wang, Ping Luan, Juan Zhang, Yu-Tao Xiang, Haijing Niu, Zhen Yuan, http://labs.vtc.vt.edu/hnl/hyperScan.html

- https://www.frontiersin.org/articles/10.3389/fpsyg.2018.01862/full

- https://www.google.com/search?q=hyperscanning&sxsrf=ACYBGNSVkLjb5YK9nNy6_JKU8oH-dxWGww:1571035304305&tbm=isch&source=iu&ictx=1&fir=TUxYnxeM-M_7kM%253A%252CAOaCe2SS_loZVM%252C_&vet=1&usg=AI4_-kSHoILiC-6DJ3XARsCKxpqFdrhMsA&sa=X&ved=2ahUKEwjQjvjJkpvlAhUO8HMBHcLuCp0Q9QEwBnoECAcQBg#imgrc=TjDApU4i7ocvMM:&vet=1



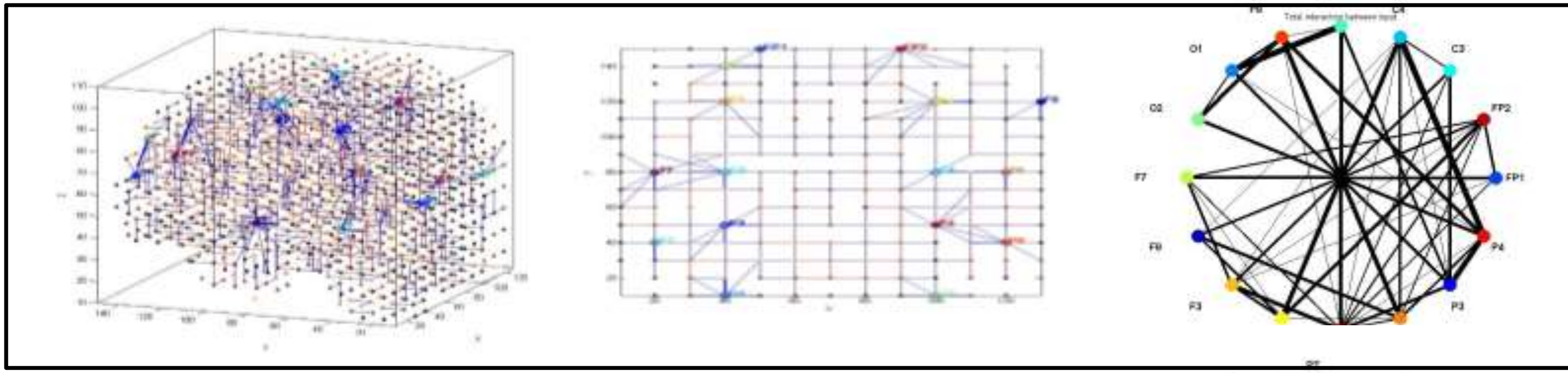
Understanding how humans synchronize and transfer knowledge between each other through hyper-scanning and using BI-SNN to model it



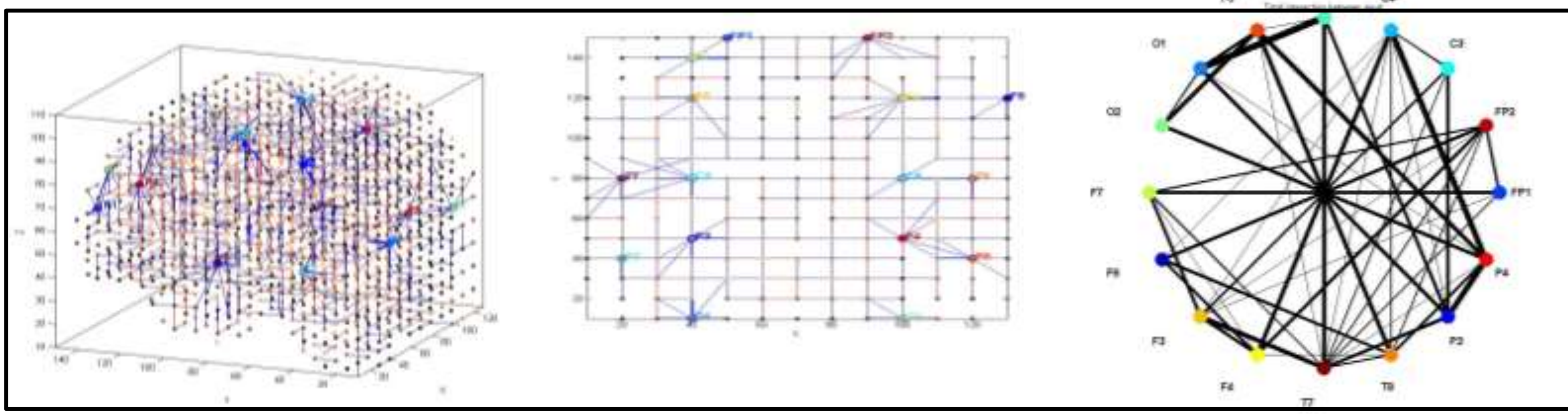
LAstolfi, J Toppi, FDe Vico Fallani, G Vecchiato, F Cincotti, C. Wilke, HYuan, D Mattia, S Salinari, B He, and F Babiloni, I, **Imaging the Social Brain by Simultaneous Hyperscanning During Subject Interaction,** EEE Intell Syst. 2011 Oct; 26 (5): 38–45.

Example: Modelling brain synchronisation through finger following experiment

-Session C
(after session of training B)
-Left finger
-Participant 1



--Right finger
-Participant 2



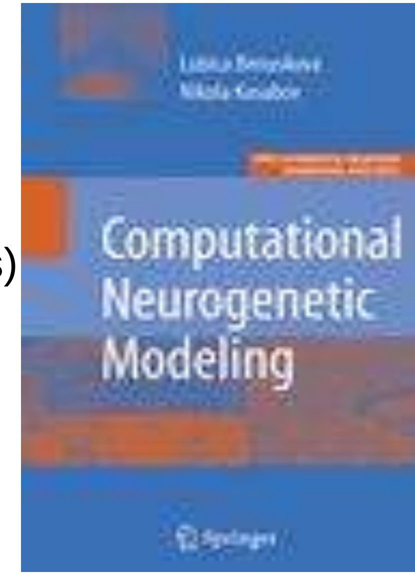
Results and findings:

(1) The difference between brain connectivity and brain spiking activity measured as EEG between two persons is smaller after a synchronisation/training (session B) measured as classification accuracy between the two brain activities (Session C, 60%) when compared with the difference between the two brain activities before synchronisation (Session A, 80%).

(2) The synchronisation is manifested mainly in the frontal and the parietal lobes.

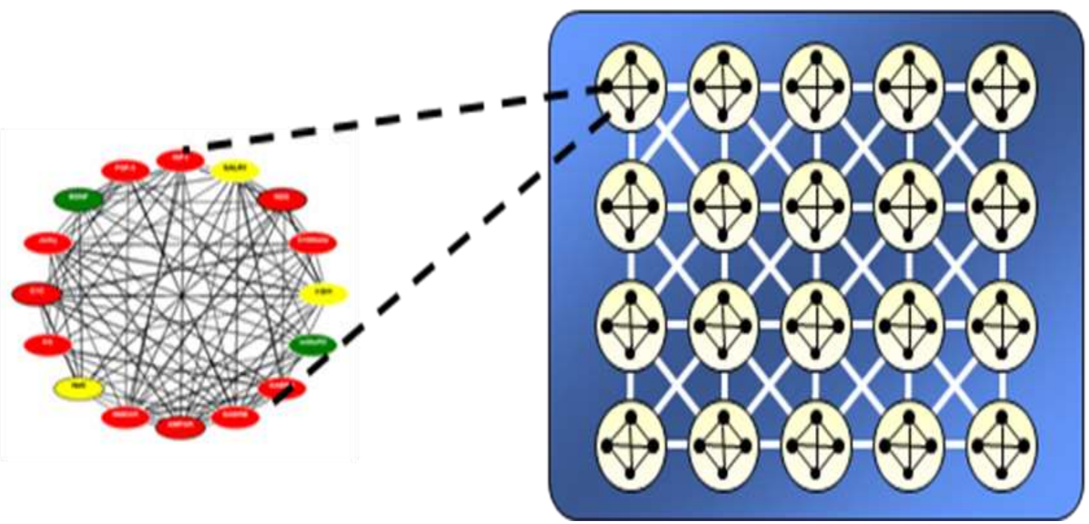
Computational Neuro-Genetic Modelling with SNN

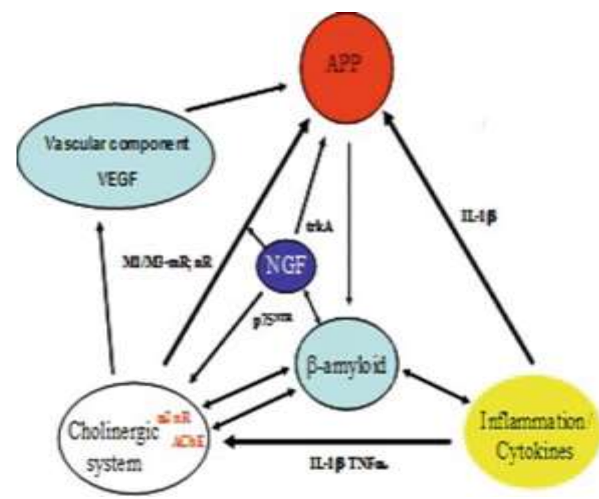
- Benuskova and Kasabov, Computational neurogenetic modelling, Springer, 2007.



- SNN incorporate a gene regulatory network (GRN) as a dynamic parameter system 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, e.g. GRN related to AD (R.Schliebs et al, SHBNI, 2014)

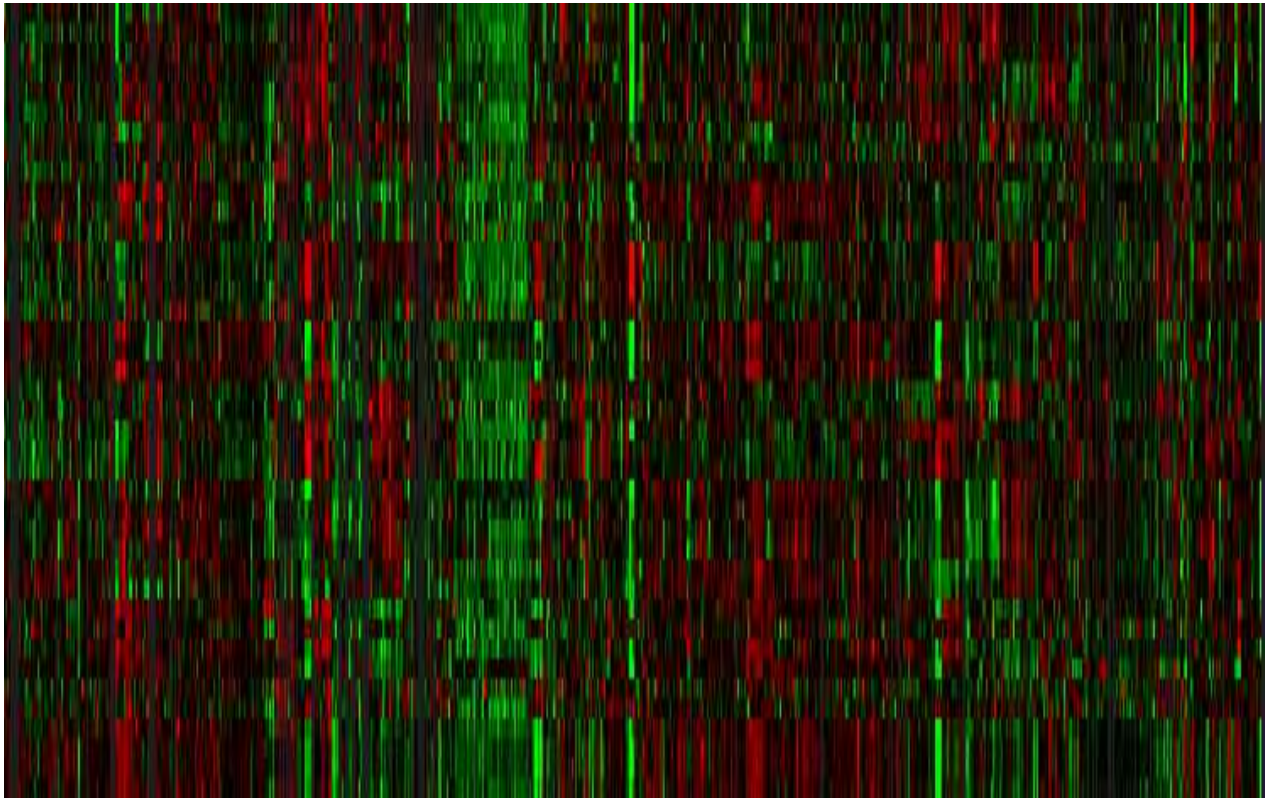
Challenge: The GRN and the SNN function at different time scales (minutes vs milliseconds) and different spatial locations.

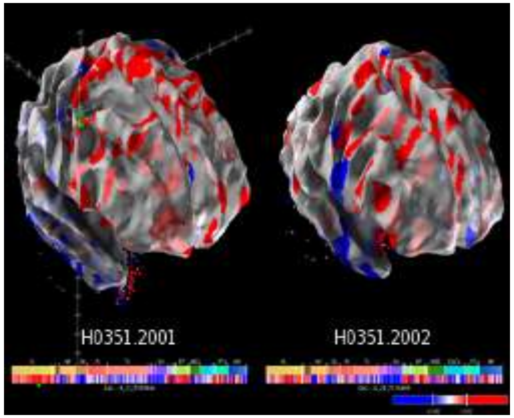




Genes are expressed differently in different parts of the brain

(http://www.brain-map.org)

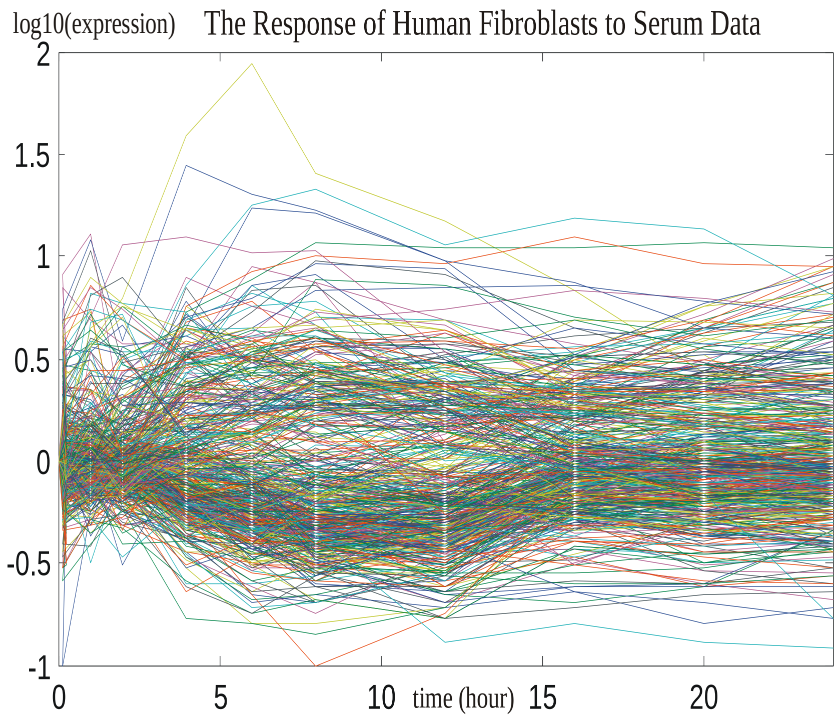


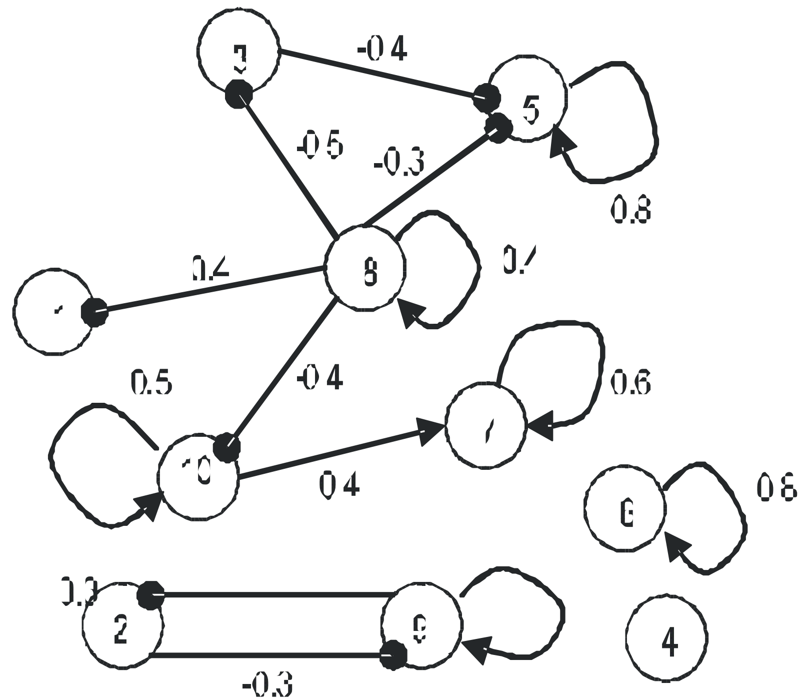


From the Brain Explorer: The Expression level of the genes (on the y-axis): ABAT A_23_P152505, ABAT A_24_P330684, ABAT CUST_52_PI416408490, ALDH5A1 A_24_P115007, ALDH5A1 A_24_P923353, ALDH5A1 A_24_P3761, AR A_23_P113111, AR CUST_16755_PI416261804, AR CUST_85_PI416408490, ARC A_23_P365738, ARC CUST_11672_PI416261804, ARC CUST_86_PI416408490, ARHGEF10 A_23_P216282, ARHGEF10 A_24_P283535, ARHGEF10 CUST_) at different slices of the brain (on the x-axis) (from www.brain-map.org) (http://www.alleninstitute.org)

Gene Regulatory Networks as Dynamical Systems

(Chan, Collins and Kasabov, JBCB, 2005)





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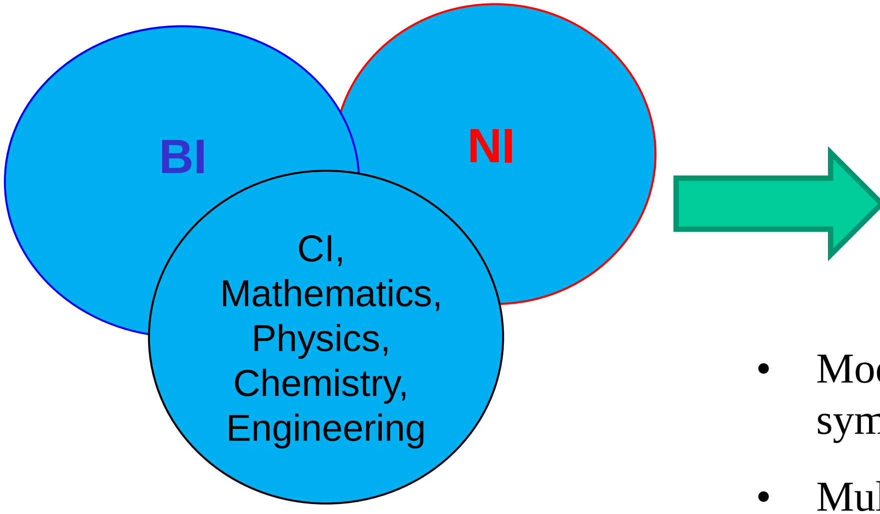
Future directions: Brain inspired AI (BI-AI)

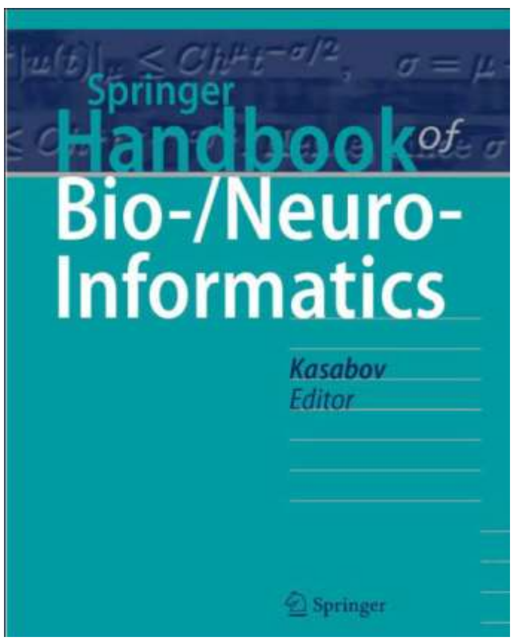


New BI-, and hybrid computational methods and systems

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

New Data Technologies Transparent AI

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



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International BI-SNN Community is growing

Intelligent Systems Research Centre -CN3
Ulster University, October 25-29, 2021

Ulster University

Thank you and Questions?

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