Deep Learning in Spiking Neural Networks of Time-Space Data: Methods, Systems, Applications

Nikola Kasabov
FIEEE, FRSNZ, FINNS, DVF RAE UK
George Moore Chair/Professor, Ulster University, UK

Professor, Auckland University of Technology

Honorary Professor University of Auckland and Teesside University UK
Doctor Honoris Causa Obuda University Budapest

nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk www.academics.aut.ac.nz/nkasabov

The Main Points:

1. Everything evolves in time and space, but how do we model time-space data (TSD)?

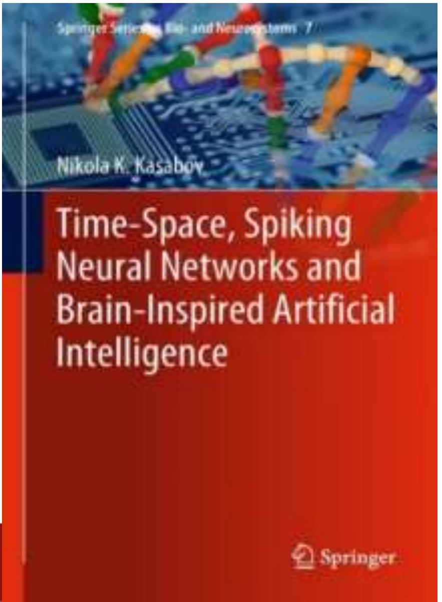
2. The human brain as the ultimate inspiration for deep learning of TSD

3. Brain-inspired spiking neural networks (BI-SNN) for deep learning of TSD and knowledge extraction. NeuCube.

4. Design and implementation of SNN systems for TSD in NeuCube. (www.kedri.aut.ac.nz/neucube and neucube.io)

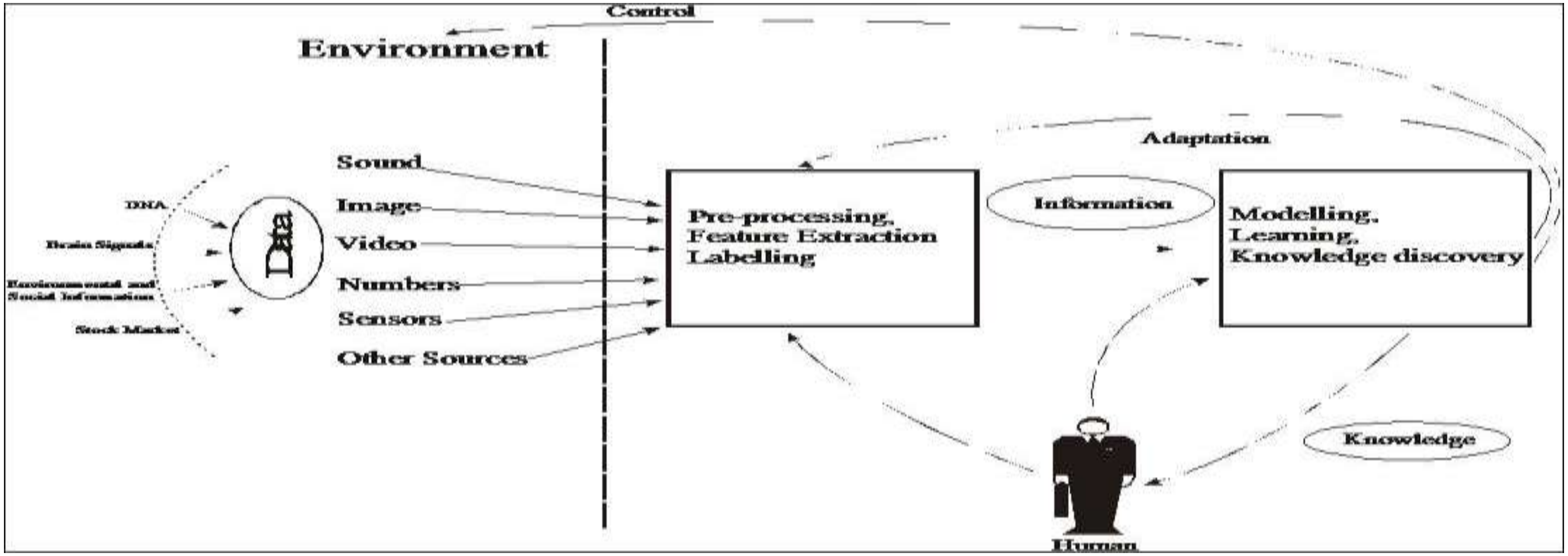
5. Applications

6. Discussions and future directions



N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019)

1. Everything evolves in Time and Space, but how do we model time-space data (TSD)?



- **S**earching: 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)

What are TSD?

Time space processes in Nature:

- Evolutionary (population/generation) processes
- Brain cognitive processes
- System information processing (environment)
- Information processing in a cell
- Molecular information processing (genes, proteins)
- Quantum information processing

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)

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).

The challenge: To better analyse, model and understand the data and the processes that generate the data.

2. **The human brain as the ultimate inspiration for deep learning of TSD**

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

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:

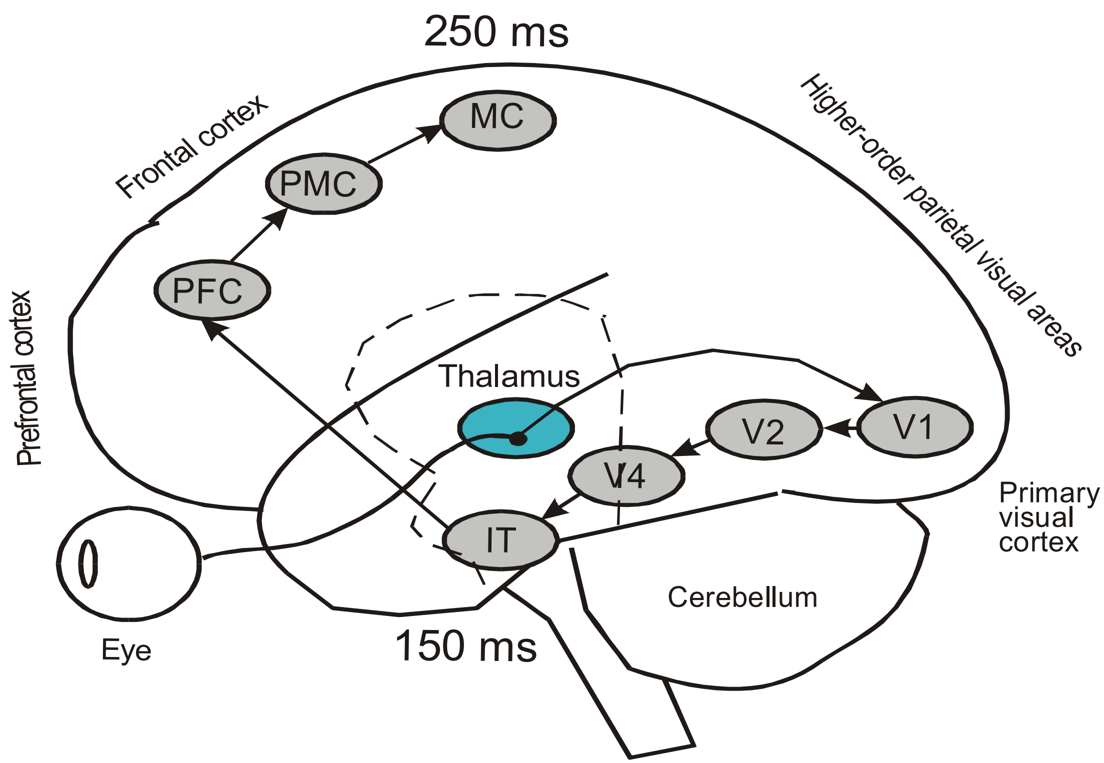
- Nanoseconds: quantum processes;
- Milliseconds: spiking activity;
- Minutes: gene expressions;
- Hours: learning in synapses;
- Many years: evolution of genes.

Spatially evolved structure with spatially allocated functions

Knowledge is represented as deep spatio-temporal patterns

nkasabov@aut.ac.nz nk.kasabov@ulster.ac.nz

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

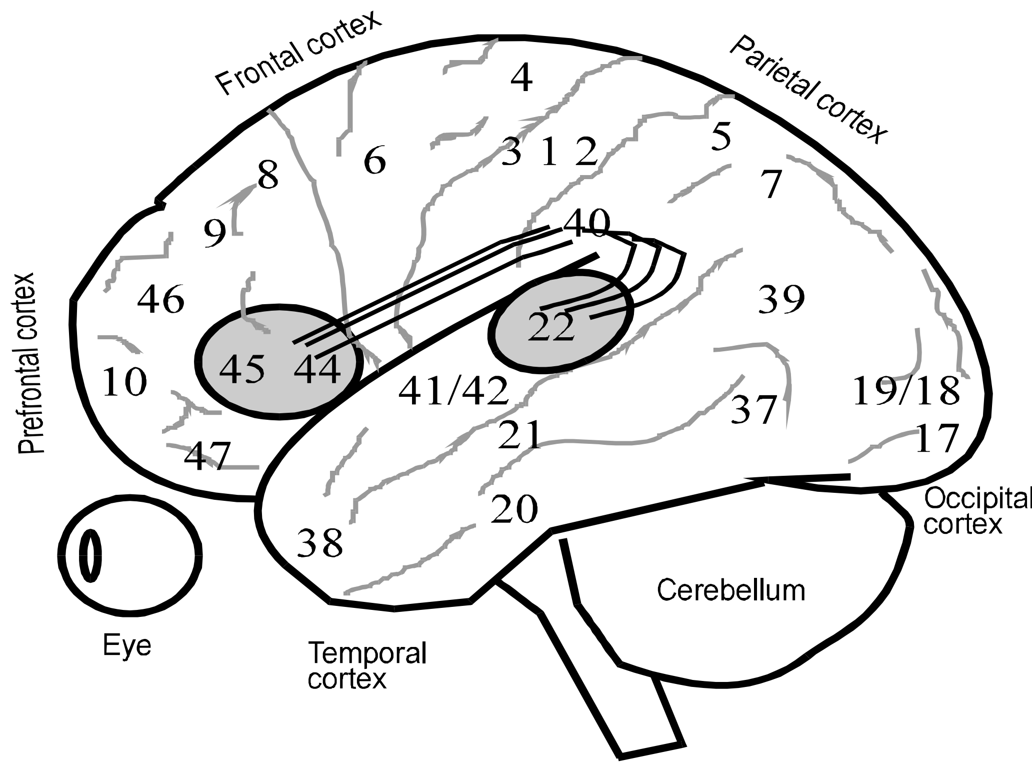


Deep serial processing of visual stimuli in humans for image classification and action.

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 in time-space

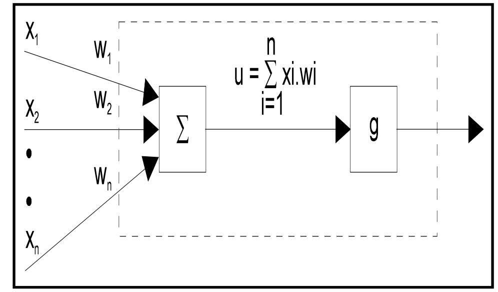


(from L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer, 2007)

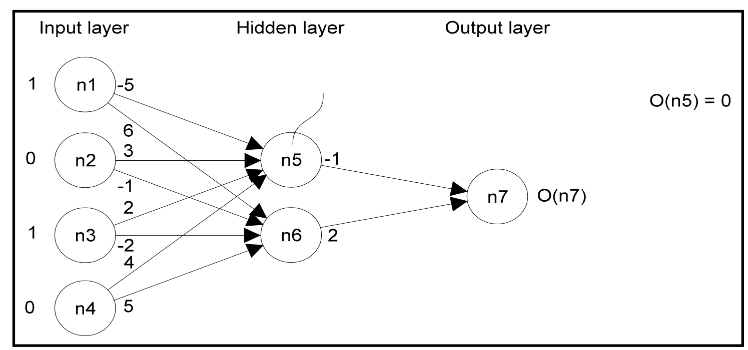
The basic model of language processing during the simple task of repeating the word that has been heard is the Wernicke-Geschwind model (Mayeux and Kandel 1991). A language task involves transfer of information from the inner ear through the auditory nucleus in thalamus to the primary auditory cortex (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.

Early 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’.



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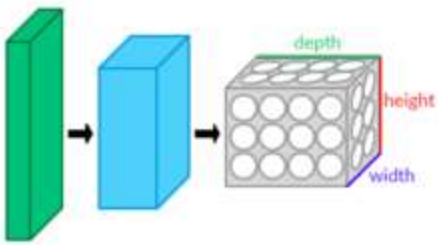
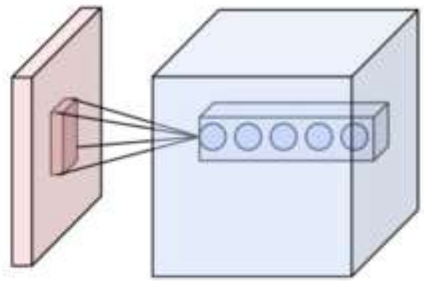
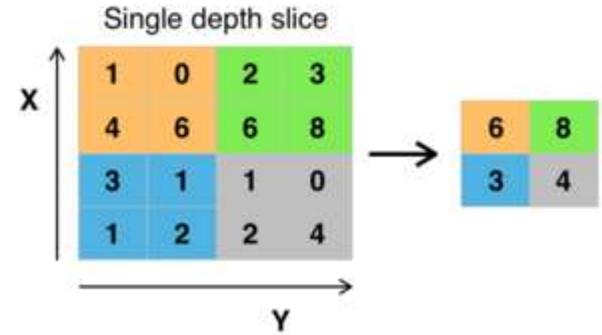
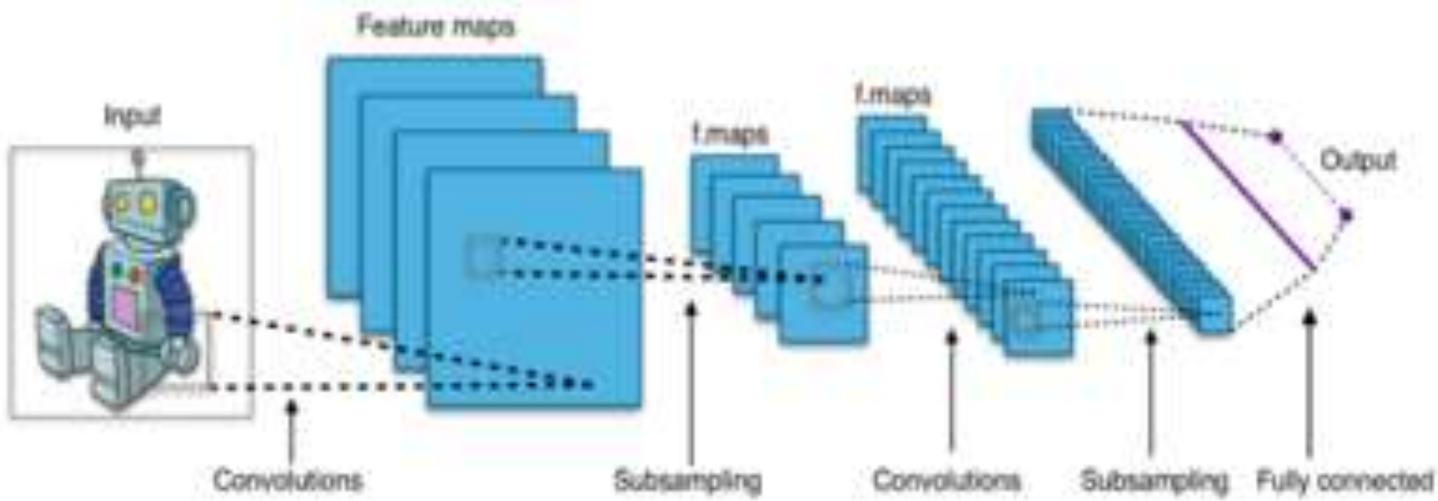
.... Deep Convolutional Neural Networks



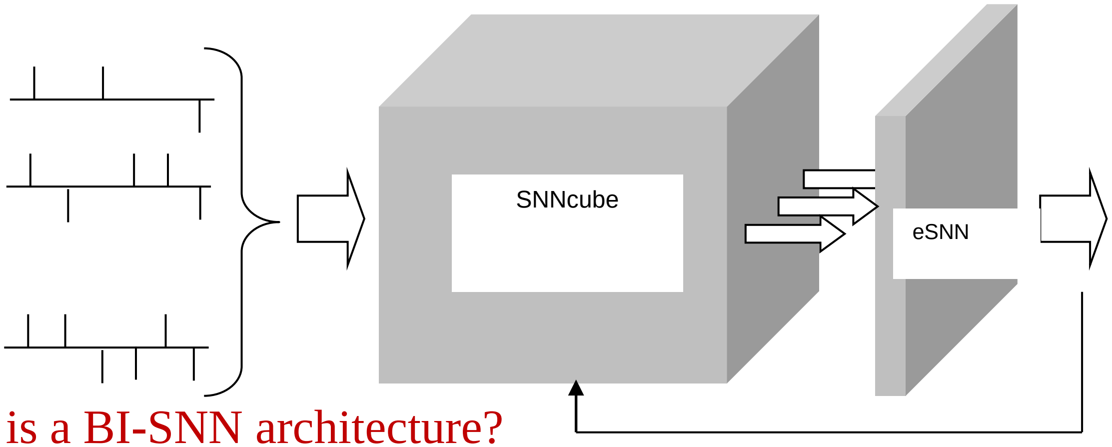


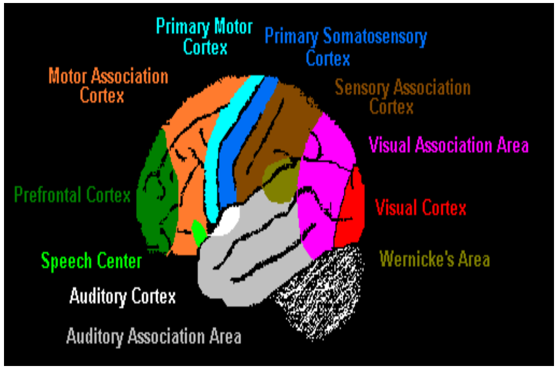




Deep NN are excellent for vector, frame- based data (e.g. image recognition) but not for TSD and for knowledge extraction.

3. Brain-inspired spiking neural networks (BI-SNN) for deep learning of TSD and knowledge extraction. NeuCube.

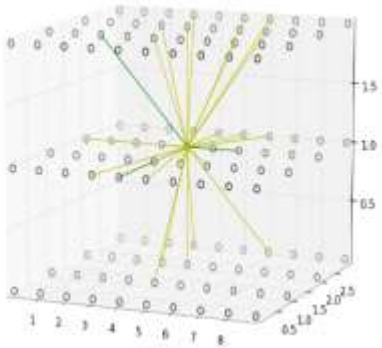




What is a BI-SNN architecture?

- 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, ….

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

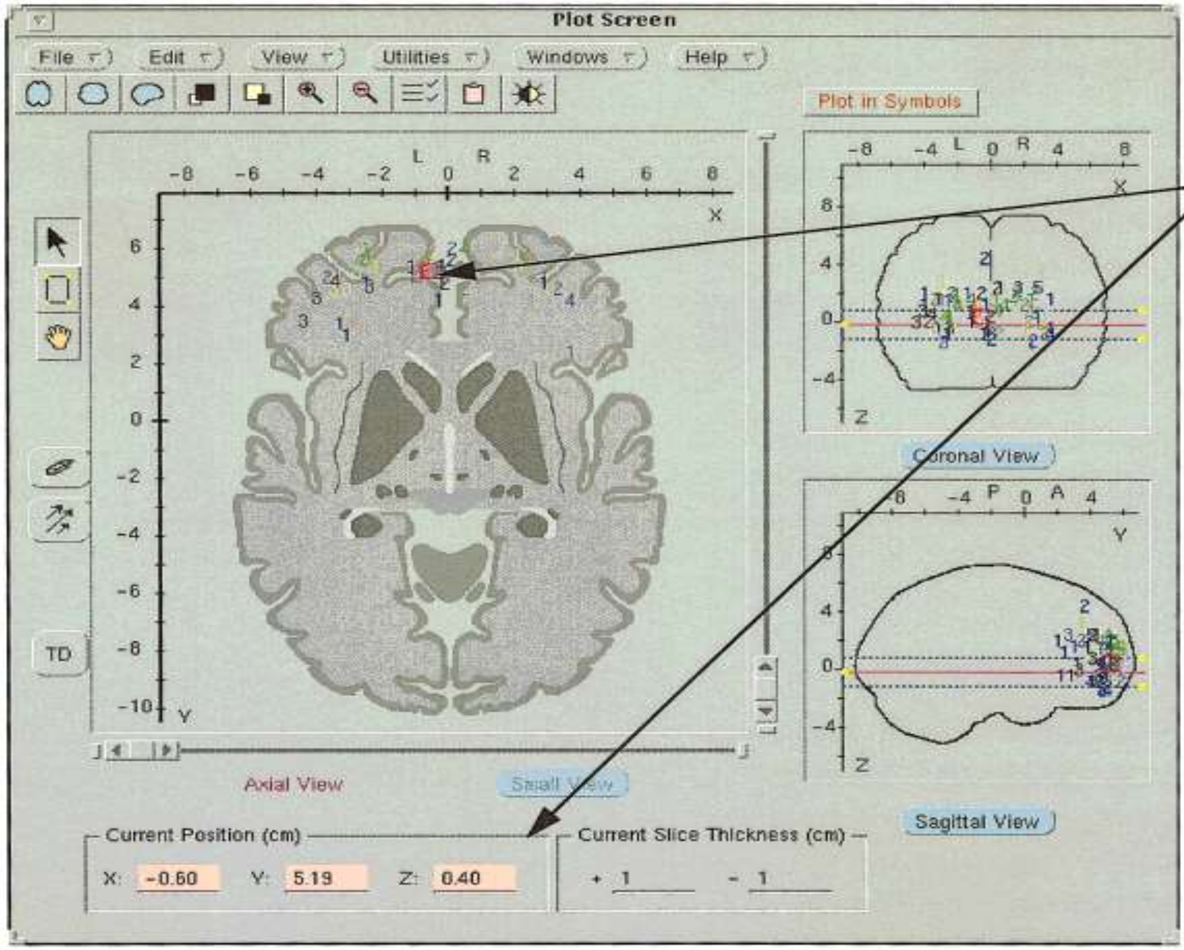


nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

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

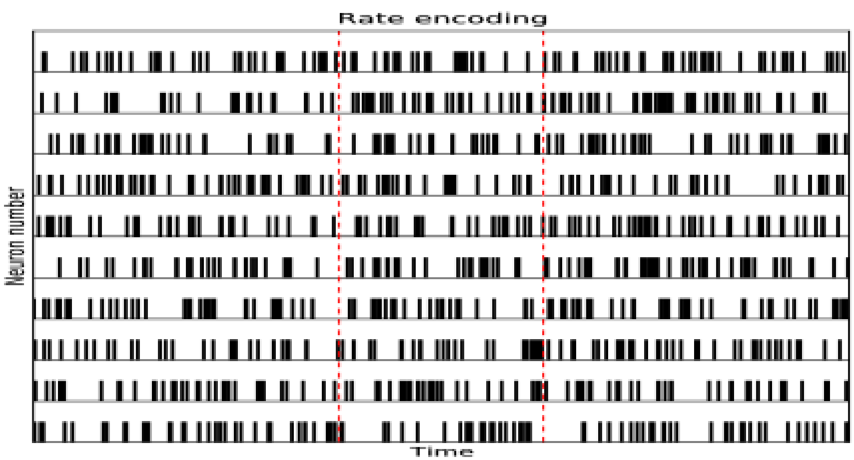
x = -6 mm
y = 52 mm
z = 4 mm

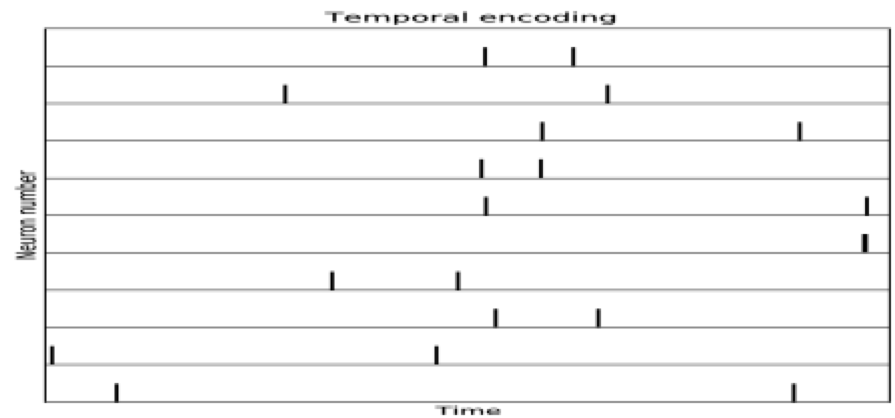
Query on Brodmann Area 10 yielded:

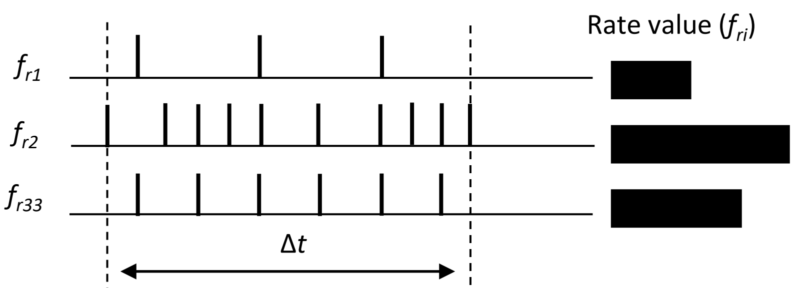
- **32 papers**
- **46 experiments**

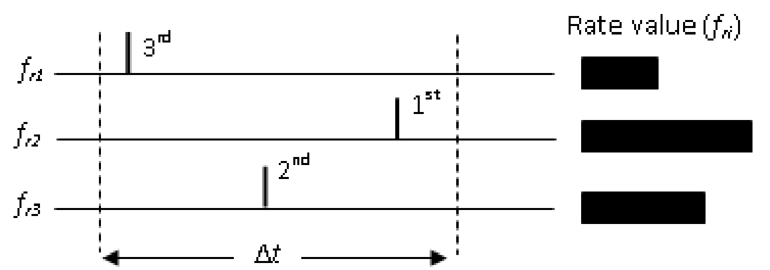
Rate vs time-based coding

- 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!









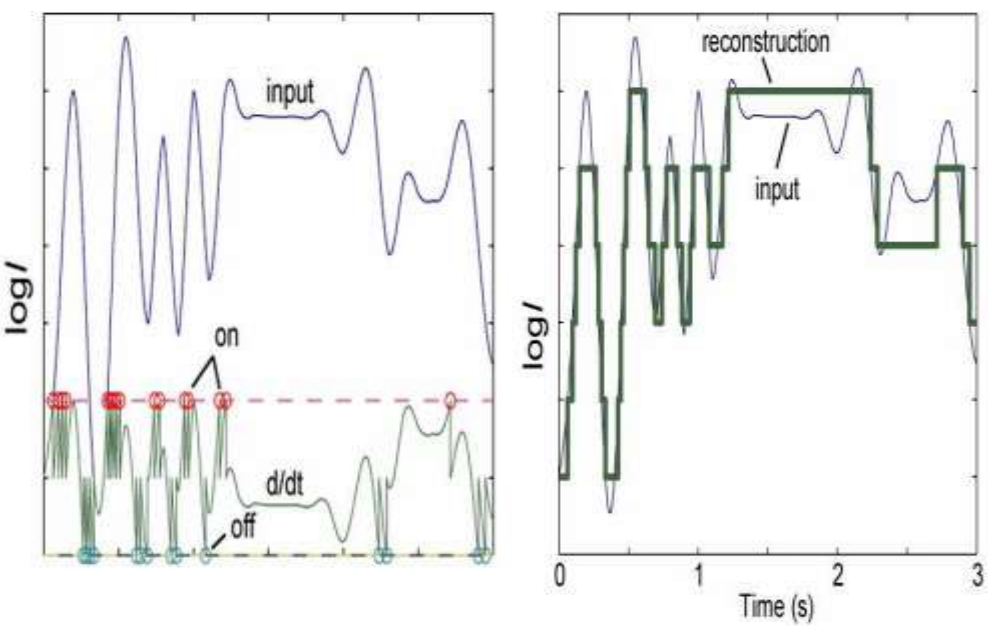
nkasabov@aut.ac.nz

Spike encoding methods

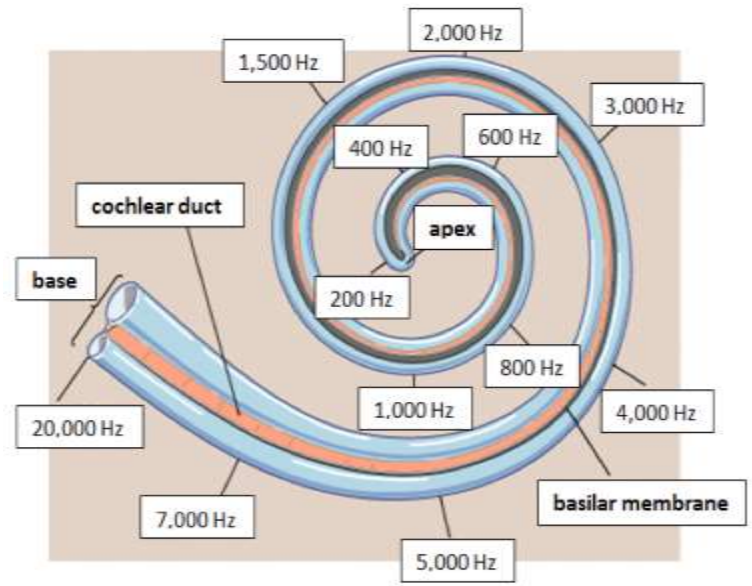
A spike is generated only if a change in the input data occurs beyond a threshold

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

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



Threshold-based encoding – retinotopic

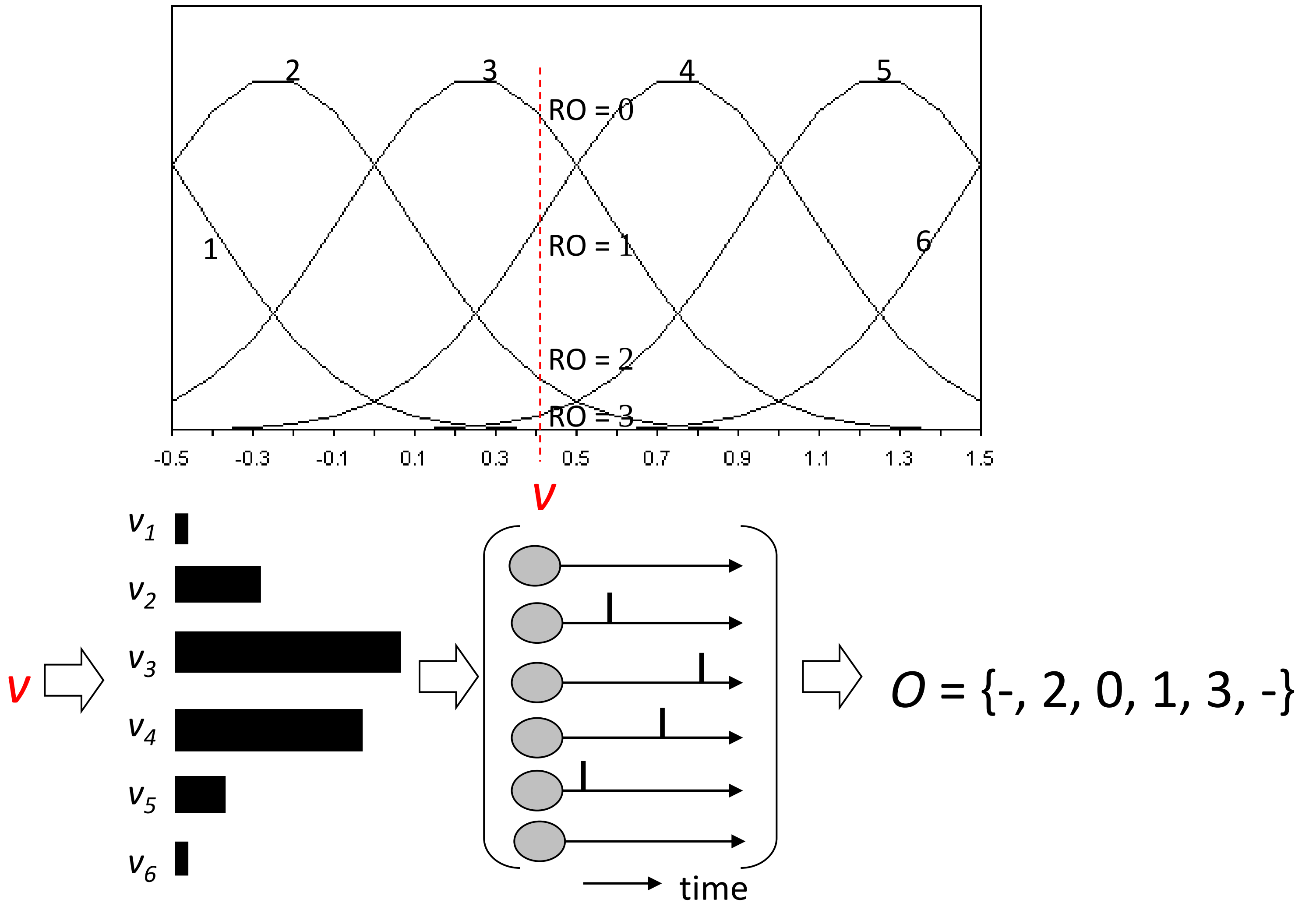


Tonotopic organization of the cochlea:
https://sites.google.com/site/jayanthinyswebite

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

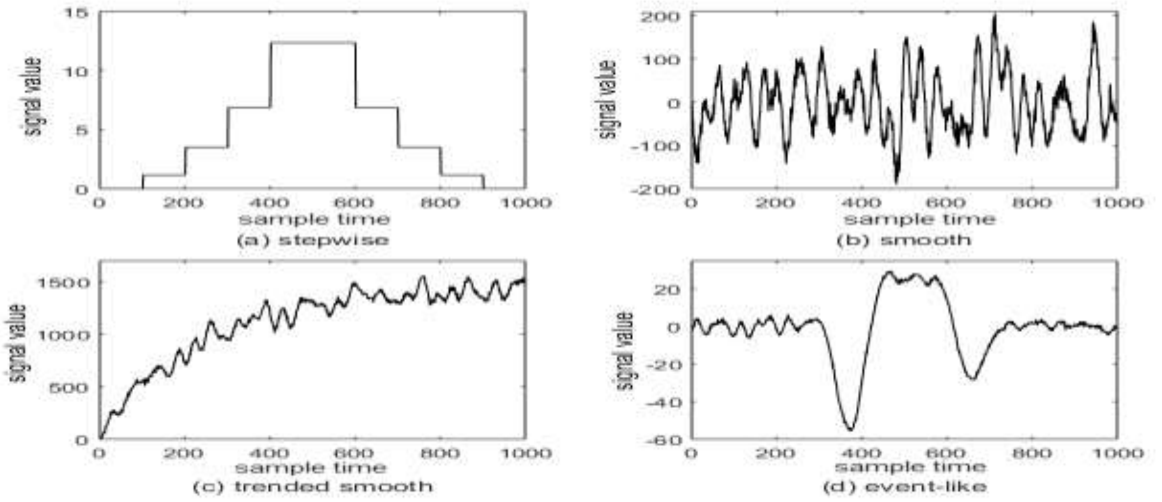
RO population coding(RO-POP C)

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



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.

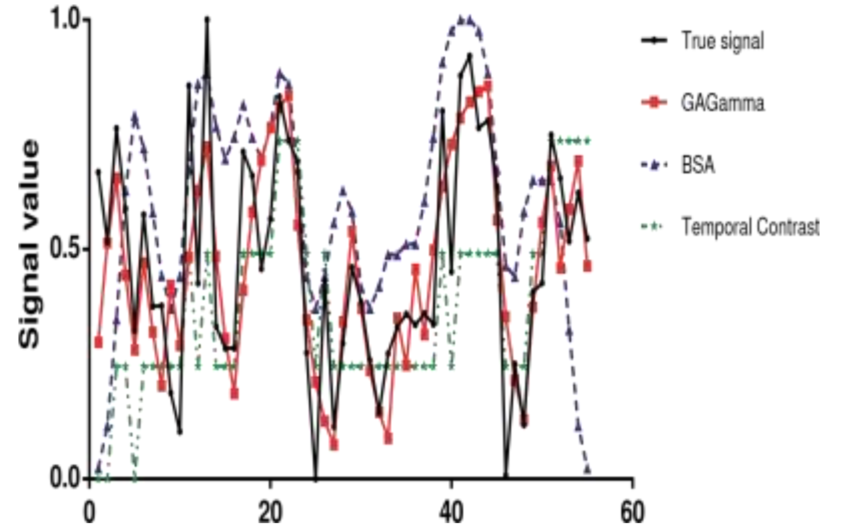
SF encoding was most effective for all types of signals as it proved to be robust and easy to optimize.

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)

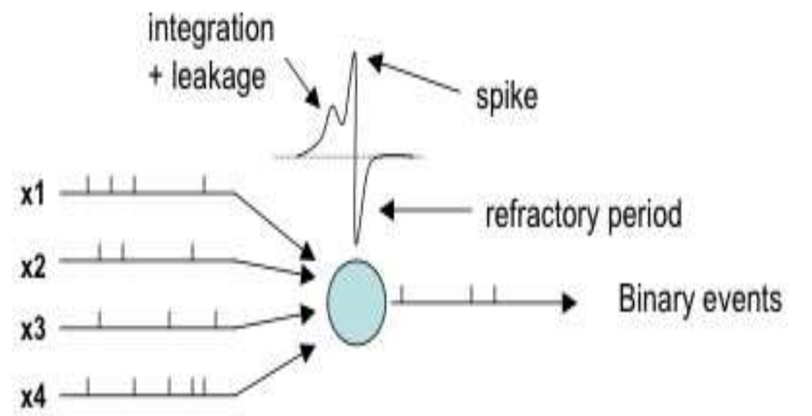


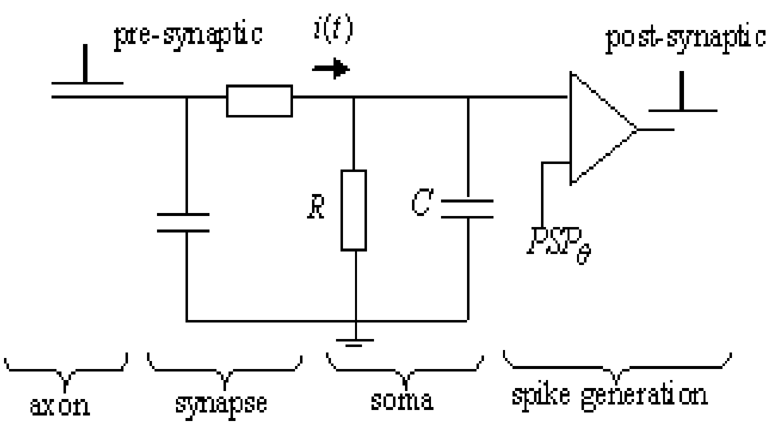
N.Sengupta, N. Kasabov, Spike-time encoding as a data compression technique for pattern recognition of temporal data, Information Sciences 406–407 (2017) 133–145.

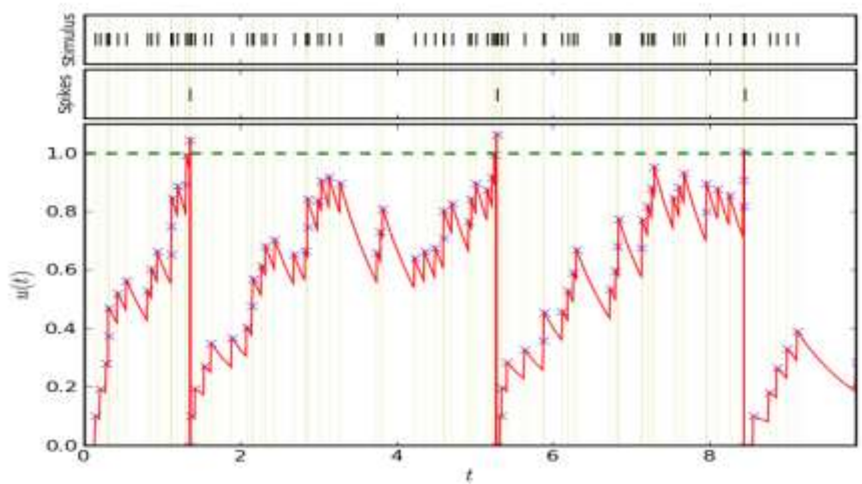
Spiking neuron models

Models of a spiking neurons and SNN

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







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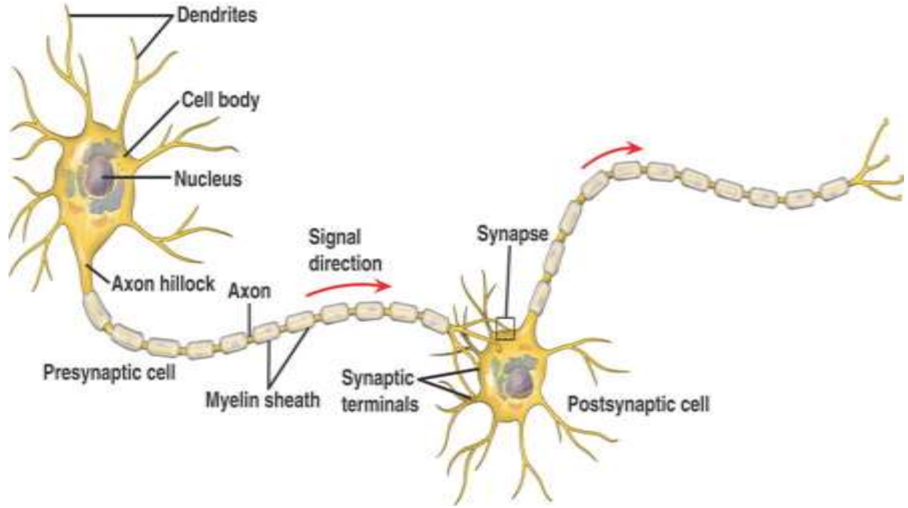
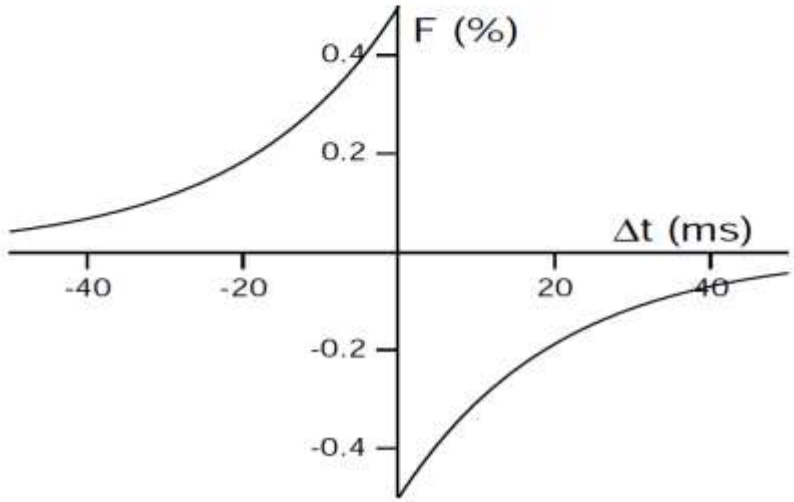
Methods for unsupervised learning in SNN

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

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



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



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

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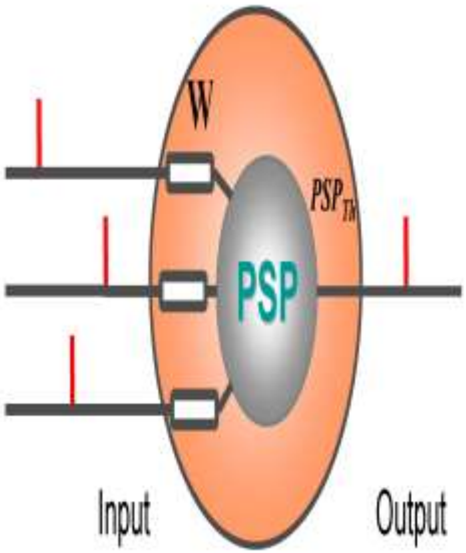
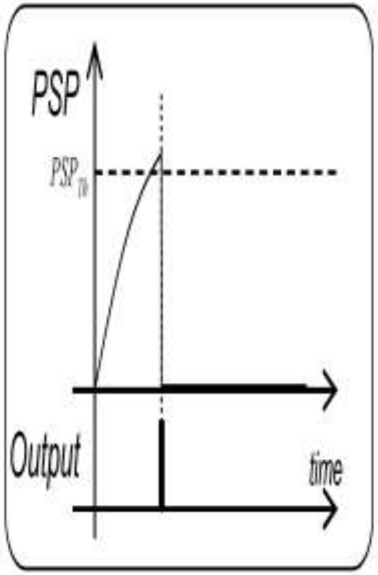
Methods for supervised learning in SNN

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





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

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

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

PSP_{Th}=C. PSPmax (T)

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

Dynamic Evolving SNN (deSNN)

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

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

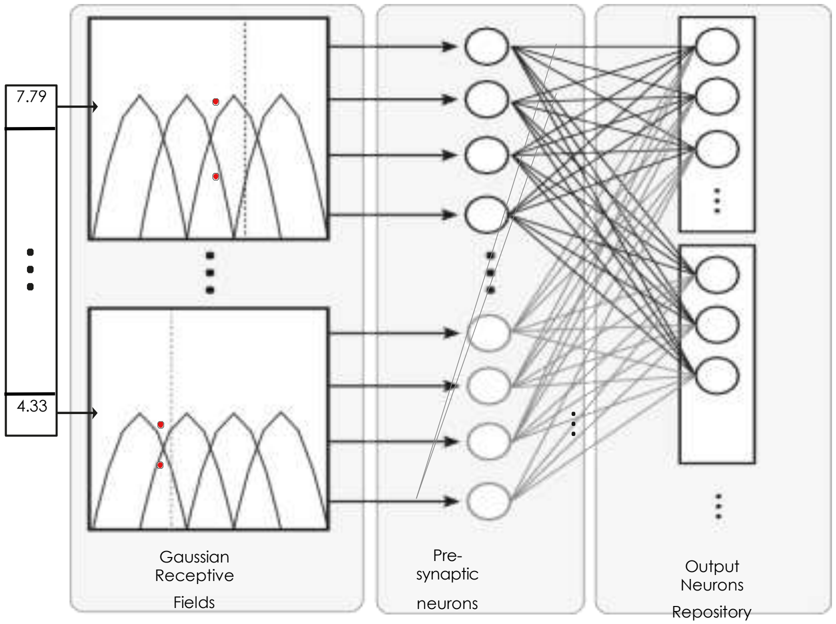
$$\Delta w_{ji} = m^{\text{order}(j)}$$

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

wj,i(t) = ej(t) · Drift

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

On-line learning in eSNN on drifting data streams



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.

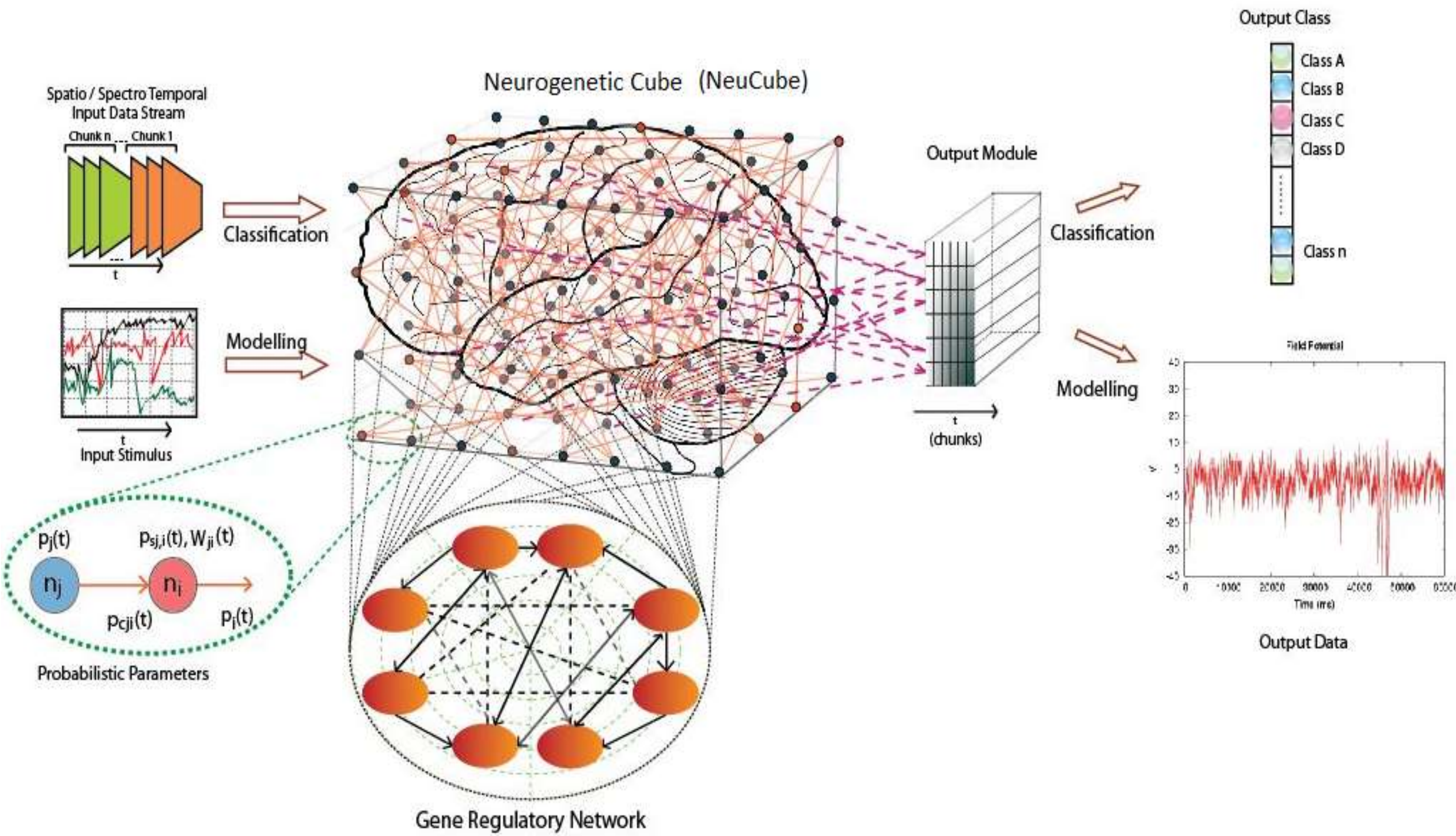
Kasabov, N., Dhoble, K., Nuntalid, N., & Indiveri, G. (2013). Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. Neural Networks, 41, 188-201 (236 citations).

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

The NeuCube Architecture



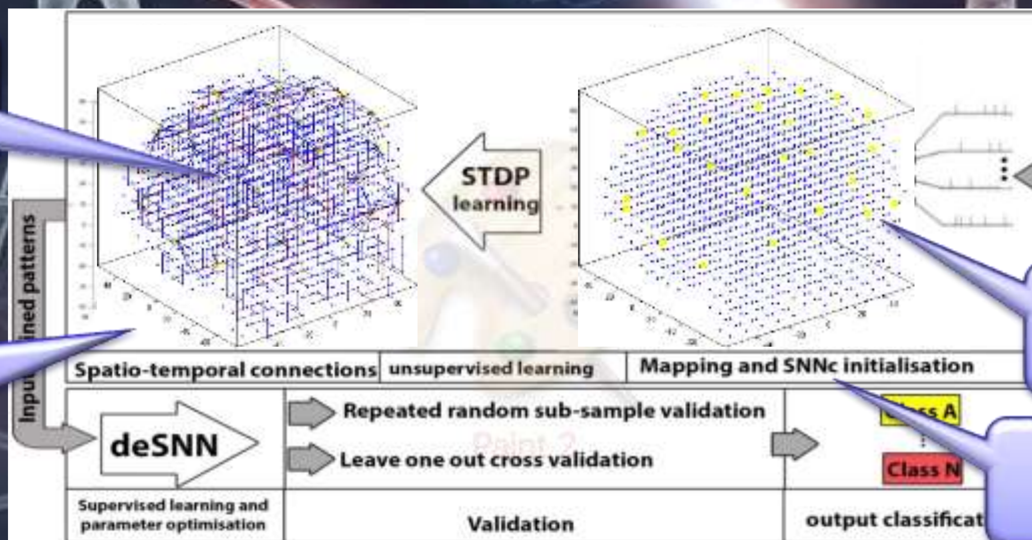
Kasabov, N., NeuCube: A Spiking Neural Network Architecture for Mapping, Learning and Understanding of Spatio-Temporal Brain Data, Neural Networks, vol.52, 2014.

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

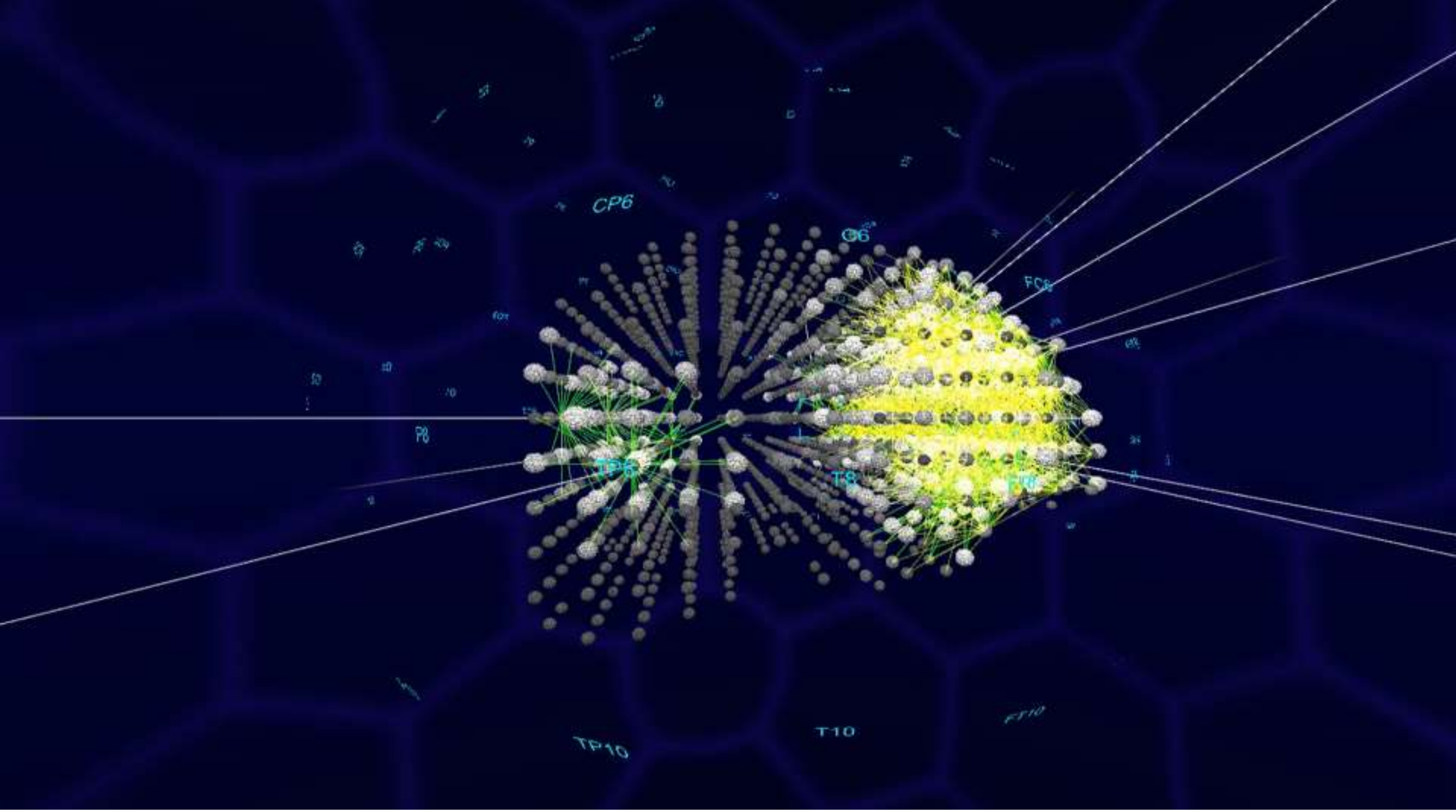
Creation of Neuron Connections During The Learning

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.

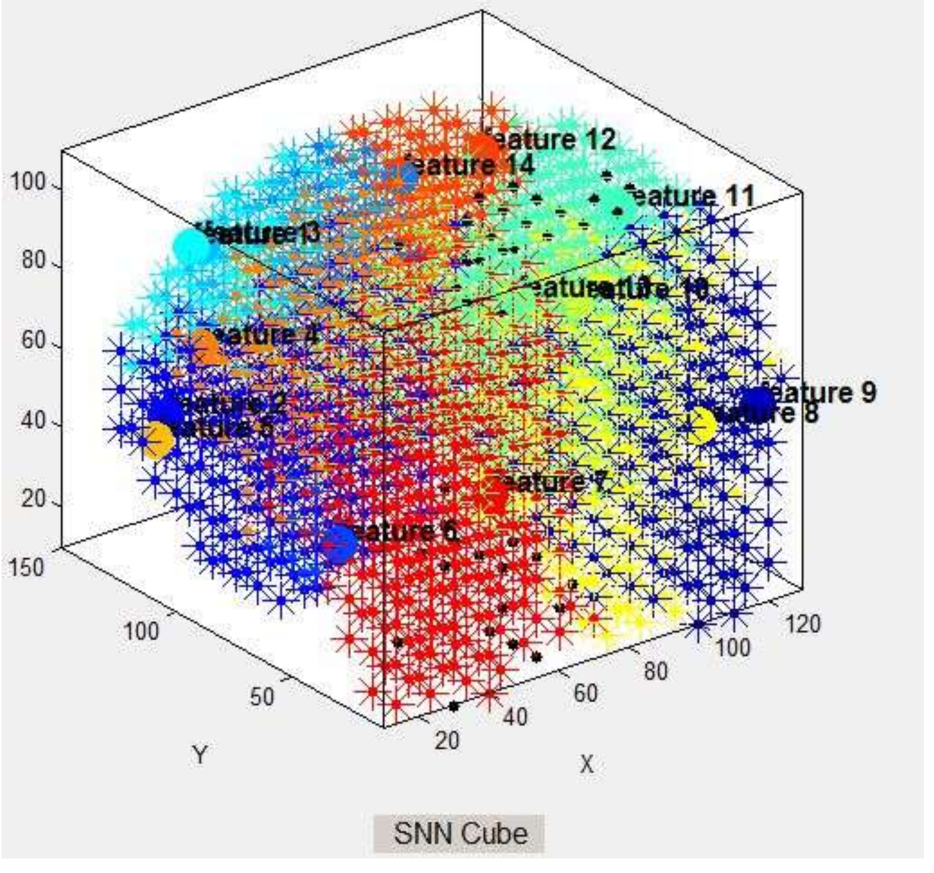
nkasabov@aut.ac.nz www.kedri.aut.ac.nz/neucube/

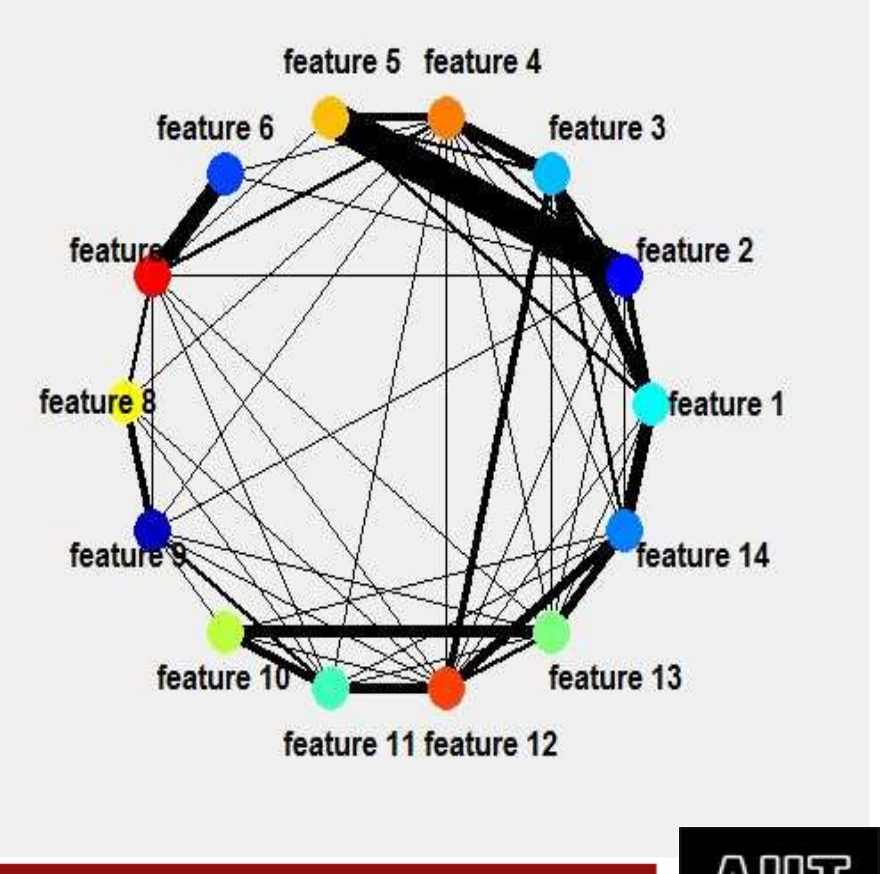
Capturing time-space knowledge as information exchange between clusters

- Clusters of highly connected neurons to input neurons;

- Clusters of spiking activity spread from input neurons ;

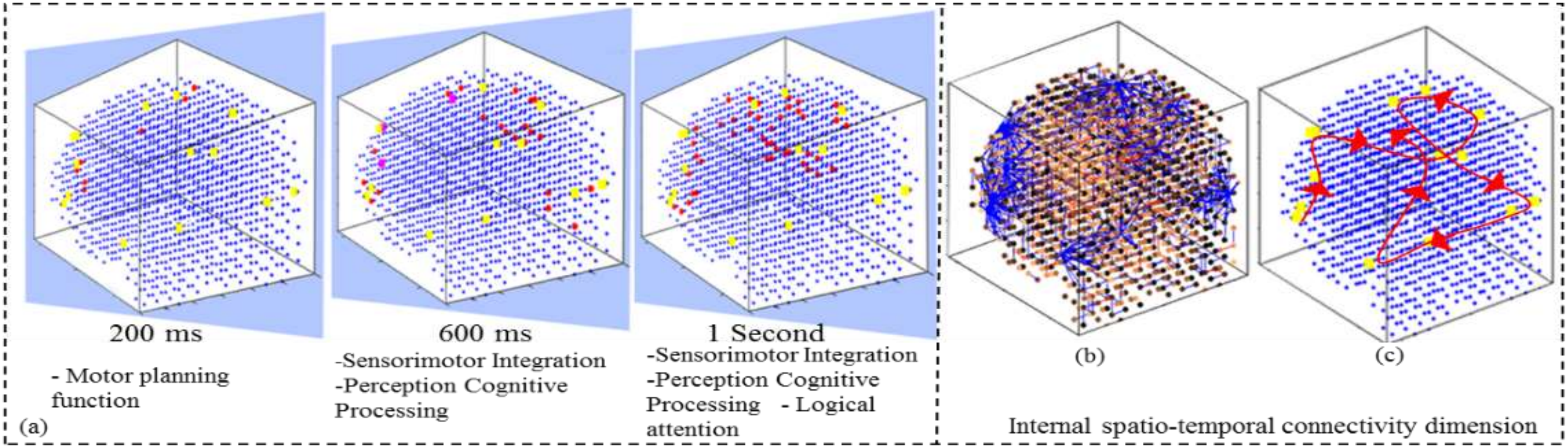
- A graph of information exchange between spatially distributed clusters around the inputs





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):

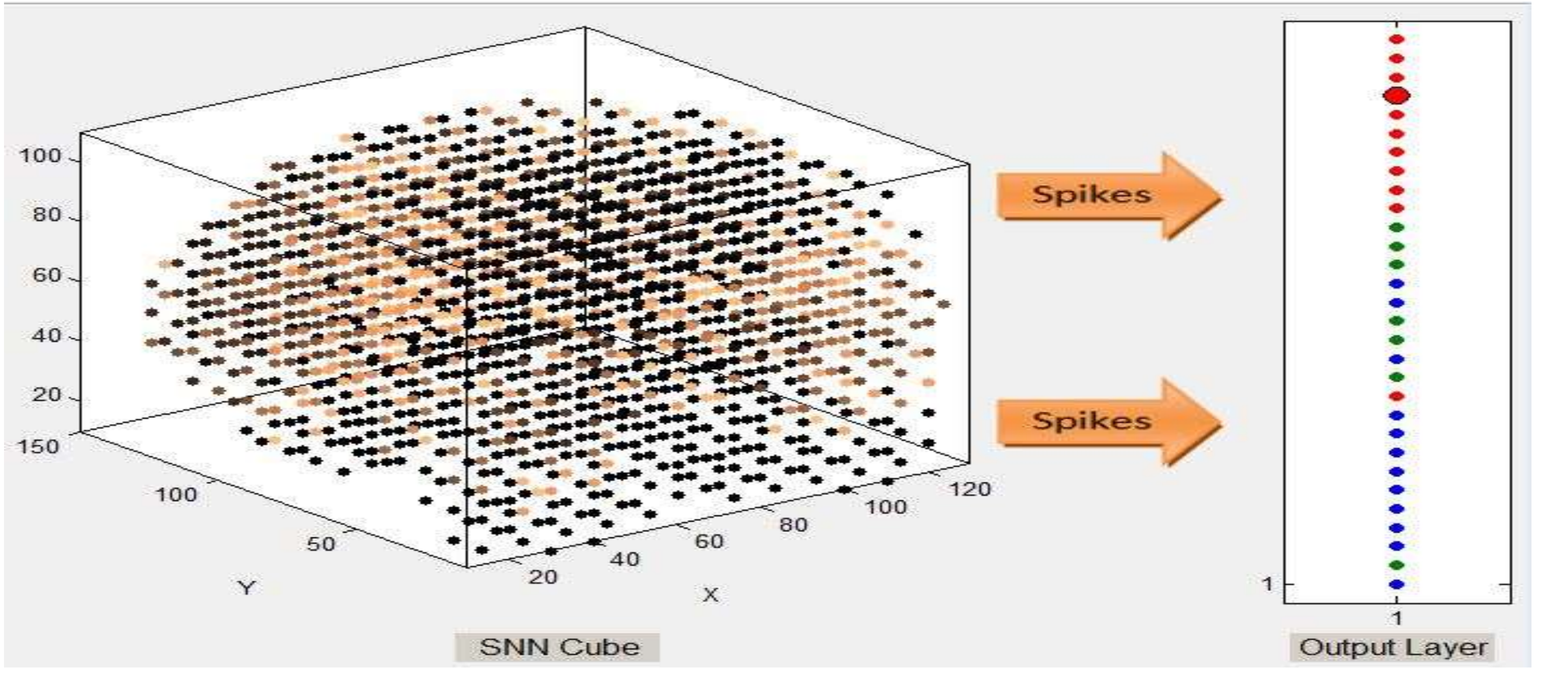
E1: Planning, in the Motor Planning functional brain area, time T1,

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).

4. Design and implementation of SNN systems for TSD

A SNN application system design procedure

- 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 TSD and possible solutions

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 development environment for SNN system design for TSD

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

NeuCube Implementations

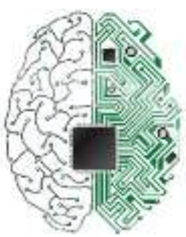
Software versions:

MATLAB Java python

Cloud

Hardware-specific versions:

RaspberryPi



Future development: NeuCube chips for AI applications

Hardware implementation of SNN:
From von Neumann principles and Atanassov's ABC Machine to Neuromorphic and Quantum Computation

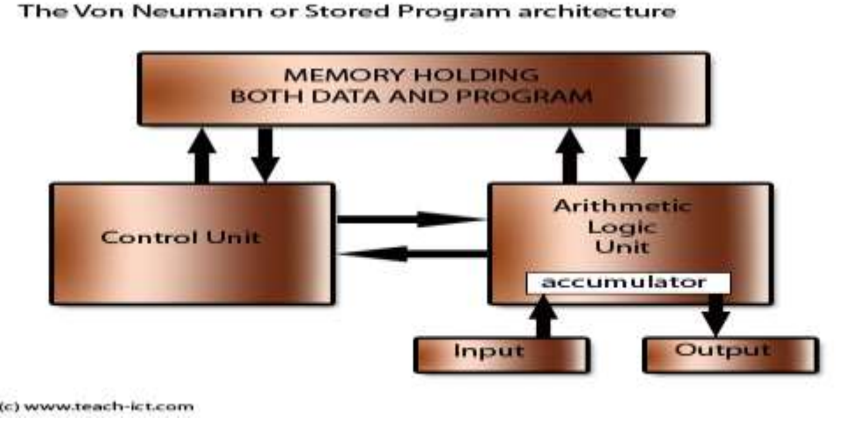
- The computer architecture of John von Neumann separates data and programmes (kept in the memory unit) from the computation (ALU); uses *bits*. First machine ABC by Atanassov and Berry.

- 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.

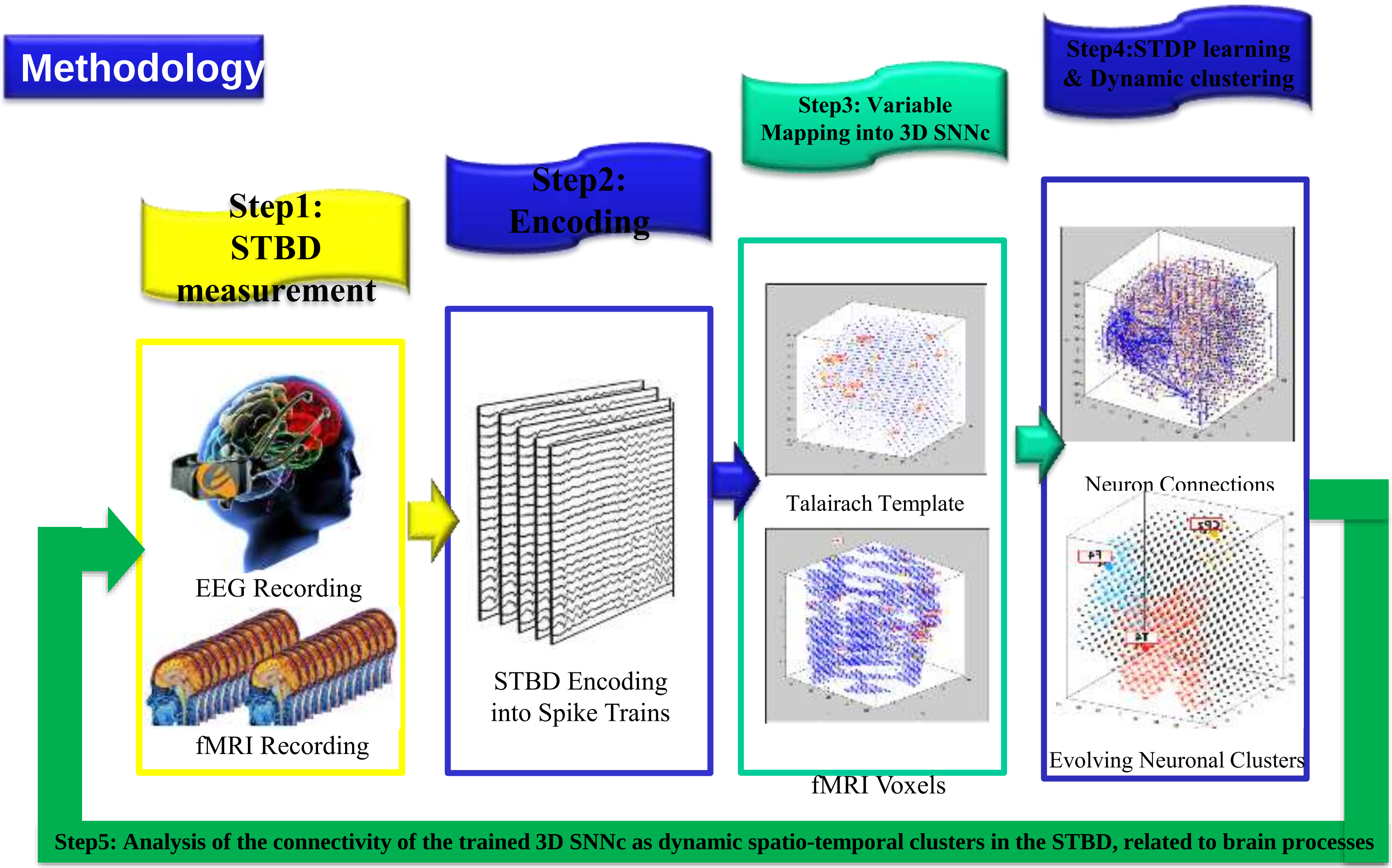
nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

5. Applications of BI-SNN for TSD

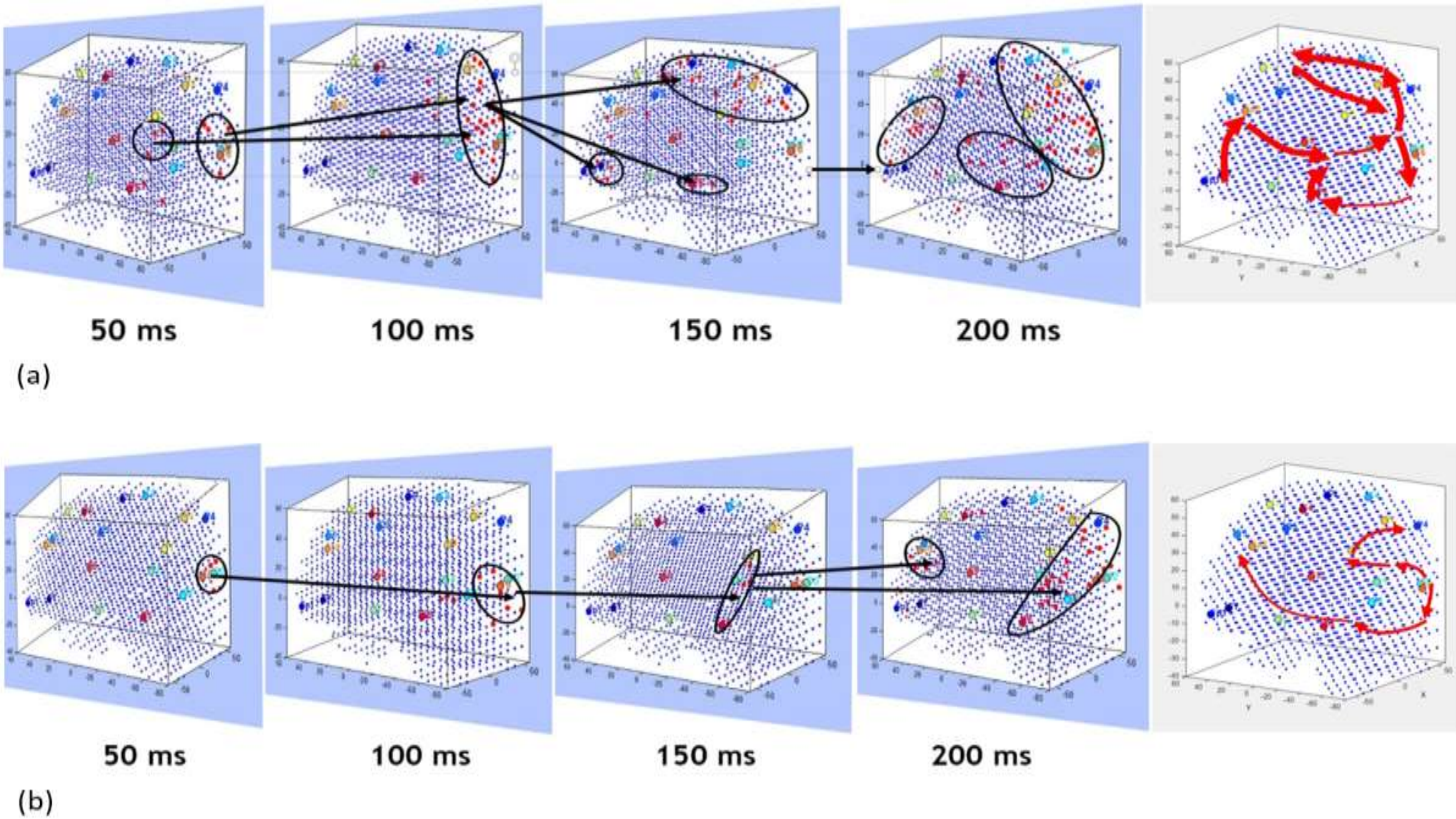
- Brain data modelling:
  - EEG: peri-perceptual modelling; mindfulness; Depression; AD; response to treatment; BCI
  - fMRI: cognitive data modelling
  - fMRI+ DTI: response to treatment
  - EEG + MRI data: epilepsy
  - neurogenetic, integrated data
- Gene expression over time
- Audio/Visual data processing
  - Speech, sound and music recognition
  - Moving object recognition
  - Language processing
- Multisensory streaming data
  - Health risk event prediction from temporal climate data (stroke)
  - Hazardous environmental event prediction (e.g. risk of earthquakes in NZ; flooding in Malaysia; pollution in London area; extreme weather from satellite images)
- Brain-Computer Interfaces and knowledge transfer between humans and machines
  - Robot control
  - Neuro-rehabilitation robots (with China Academy of Sciences)

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)

Learning and representation of brain TSD (EEG, fMRI, DTI, genetic,..)

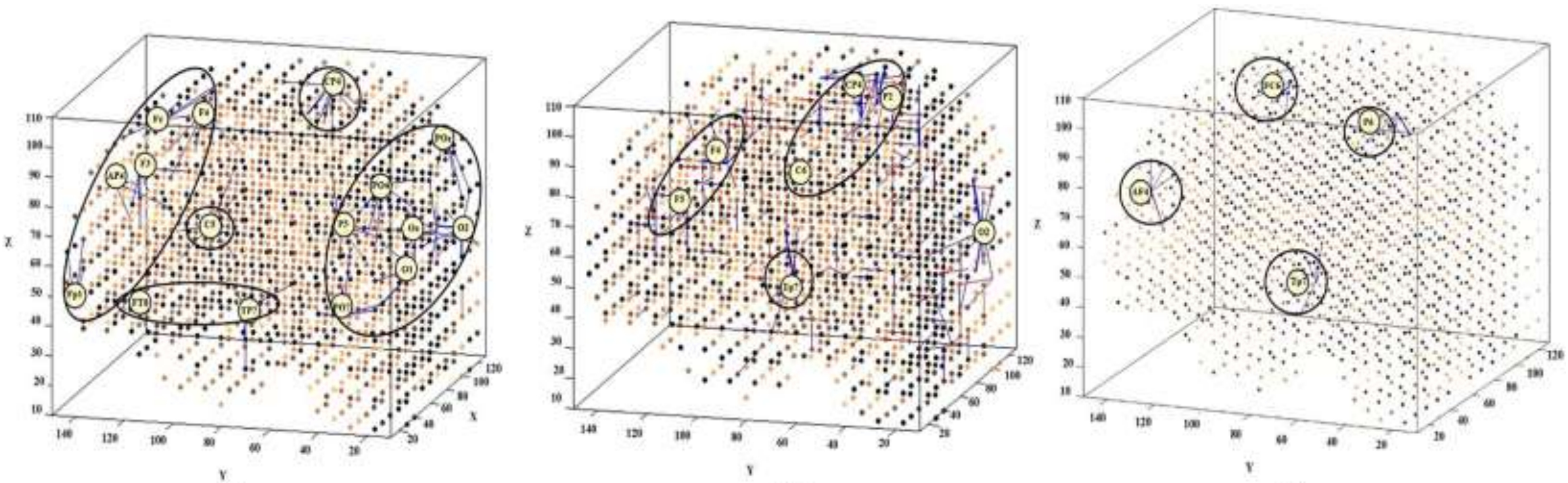


Tracing the brain dynamics in a NeuCube model



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



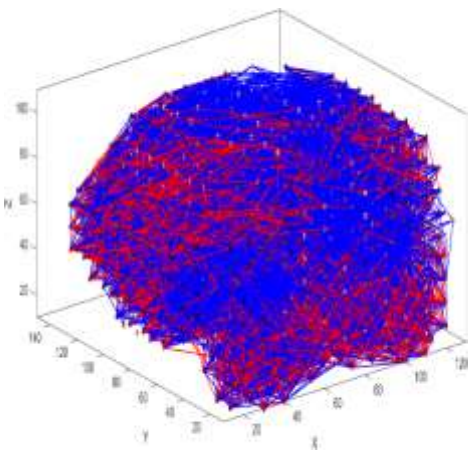
(a) (b) (c)

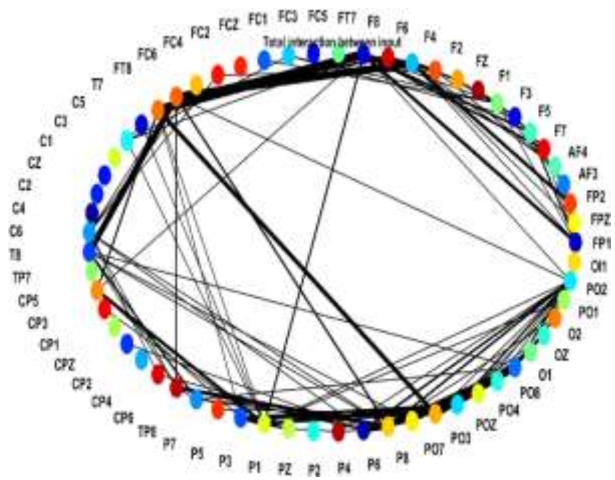
Differences between the connectivity in the trained SNN models of T1 (prior to MT) and T2 (post training) in (**a**) non-depressed (ND) group, (**b**) responsive-depressed (D+) group, and (**c**) unresponsive depressed (D−) group. The connections in each neural cluster represent the areas of main changes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

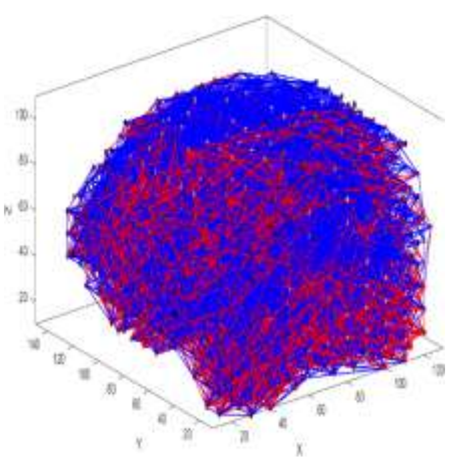
Z. Doborjeh, M. Doborjeh, T. Taylor, N. Kasabov, G. Y. Wang, R. Siegert, A. Sumich, Spiking Neural Network Modelling Approach Reveals How Mindfulness Training Rewires the Brain, **Nature,** Scientific Reports, (2019) 9: 6367, https://www.nature.com/articles/s41598-019-42863-x (top 50 papers for 2019)

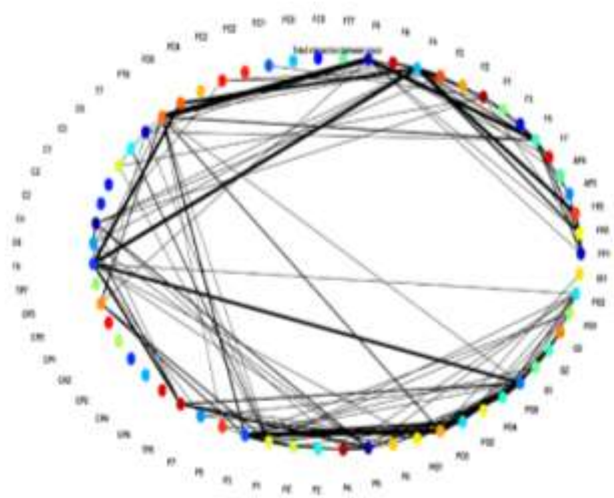
Learning and representation of EEG data for a better understanding of depression

D Shah, G Wang, M Doborjeh, Z Doborjeh, N Kasabov, ICONIP 2019, Sydney 12-15.12.2019









Visualization for eyes open state:

(a) NeuCube connectivity and FIN when a system is trained on only on depressed subjects EEG data;

(b) NeuCube connectivity and FIN when a systems is trained only on healthy subjects data.

Findings/knowledge discovered

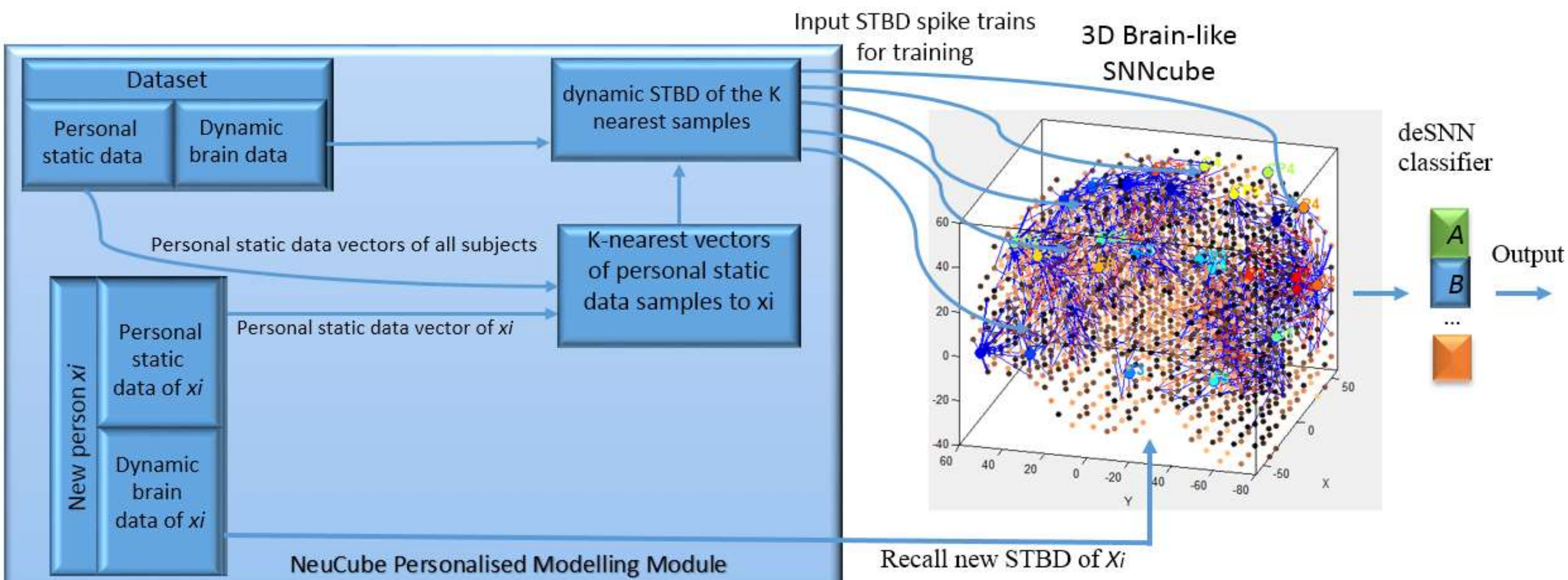
- A strong interaction F4-T8-PO8 across the right hemisphere in the healthy group is absent in the depressed group.
- There are more right frontal interactions in the depressed group including F4, F6, F8, FC4, FC6, and FC8 as compared to the healthy group indicating more negative perception in the brain.
- Long-range interaction between FT8-PO7 and F8-P1 in the depressed group.

nkasabov@aut.ac.nz

Personalised modelling (PM) using both static and spatio-temporal EEG data

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

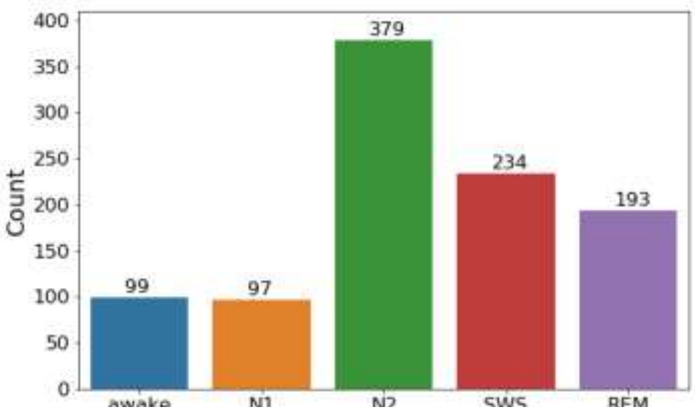
M. Doborjeh, N. Kasabov, Z. Doborjeh, R. Enayatollahi, E. Tu, A. H. Gandomi, Personalised modelling with spiking neural networks integrating temporal and static information, Neural Networks, 119 (2019),162-177.

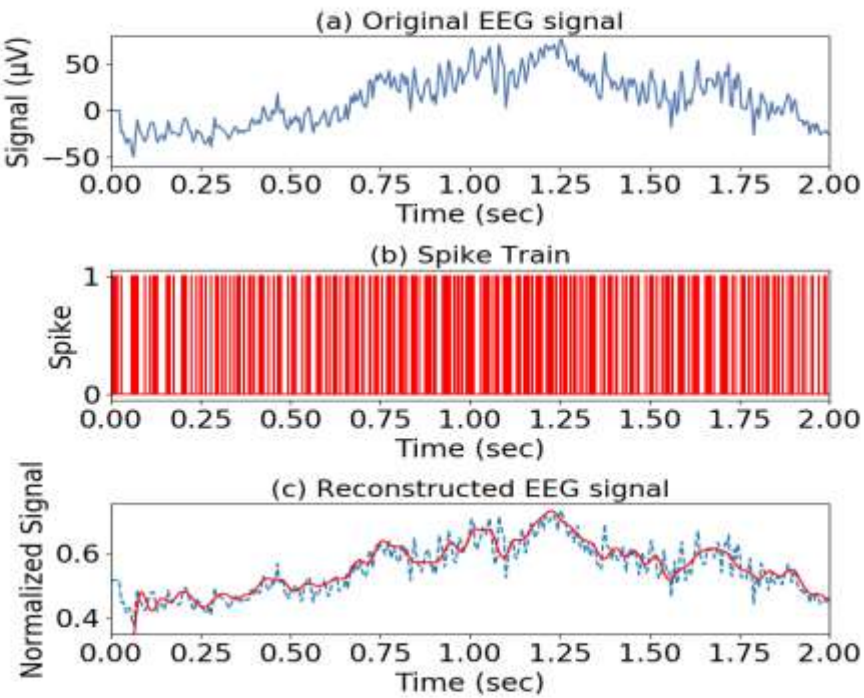


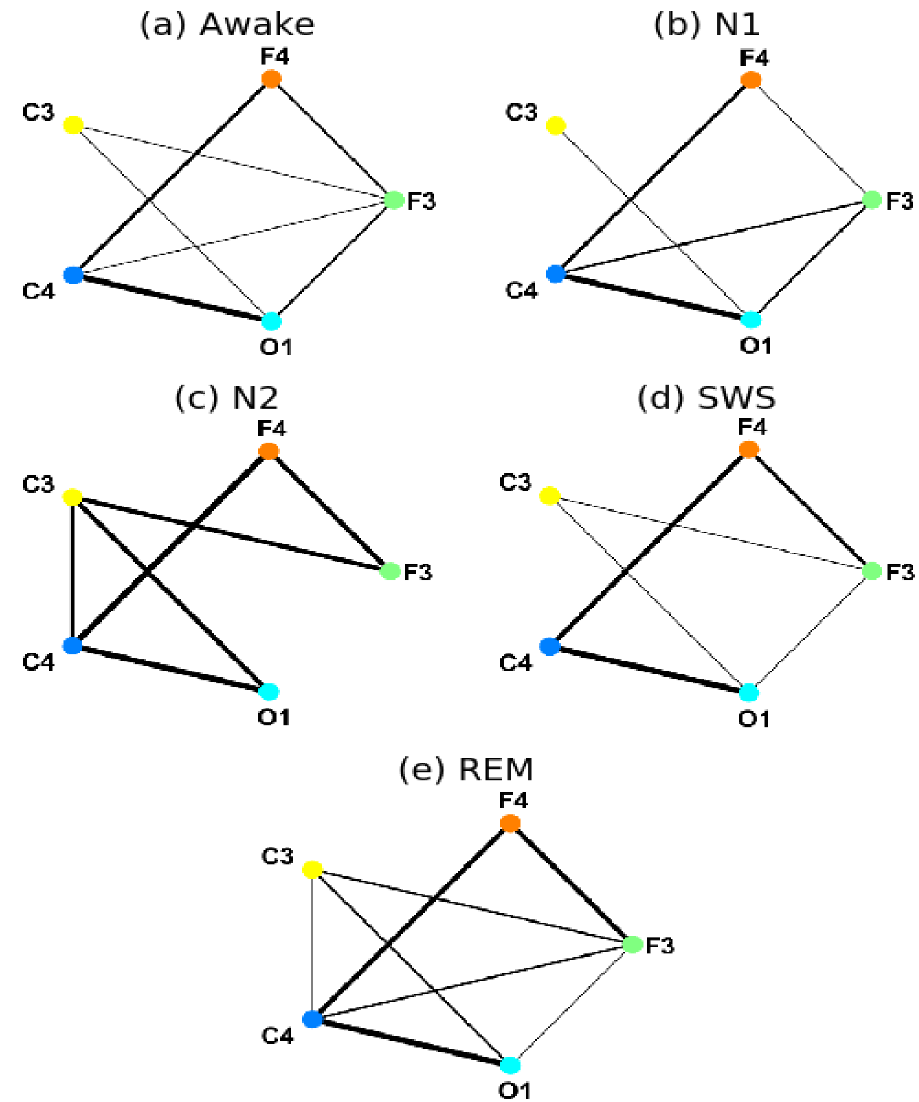
Methods	NeuCube-Personalised modelling	NeuCube- Global modelling
Classification accuracy of class M versus class OP in %	Averaged over 47 trained PSNN models: 93.61	One trained SNN model using all subjects and tested via leave-one-out method: 79.00

Sleep Stage Classification using EEG and NeuCube

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



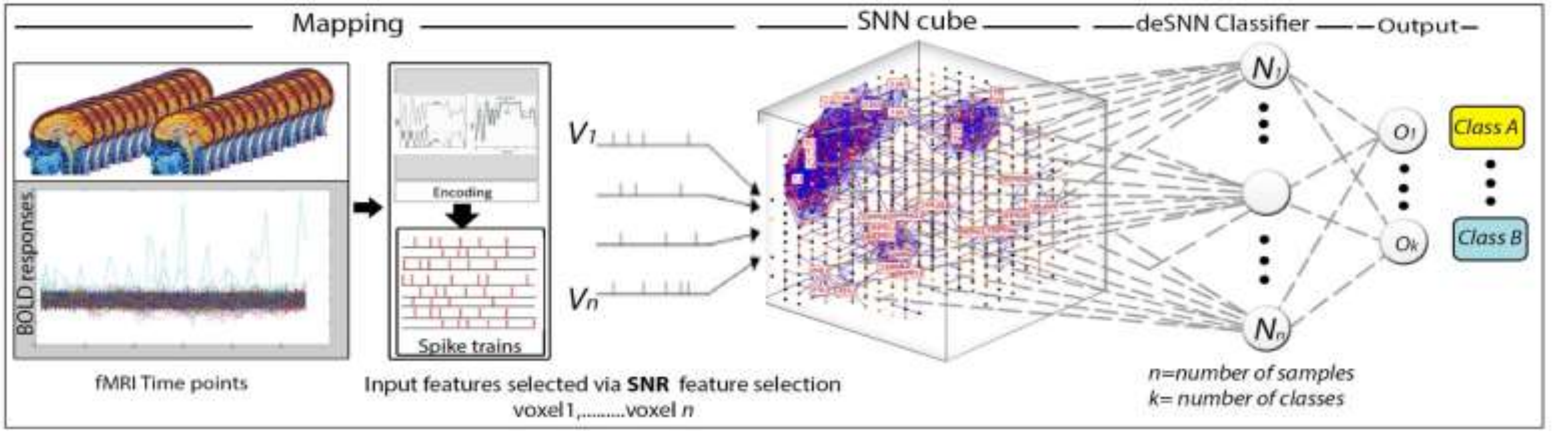




Deep learning and knowledge representation of fMRI TSD

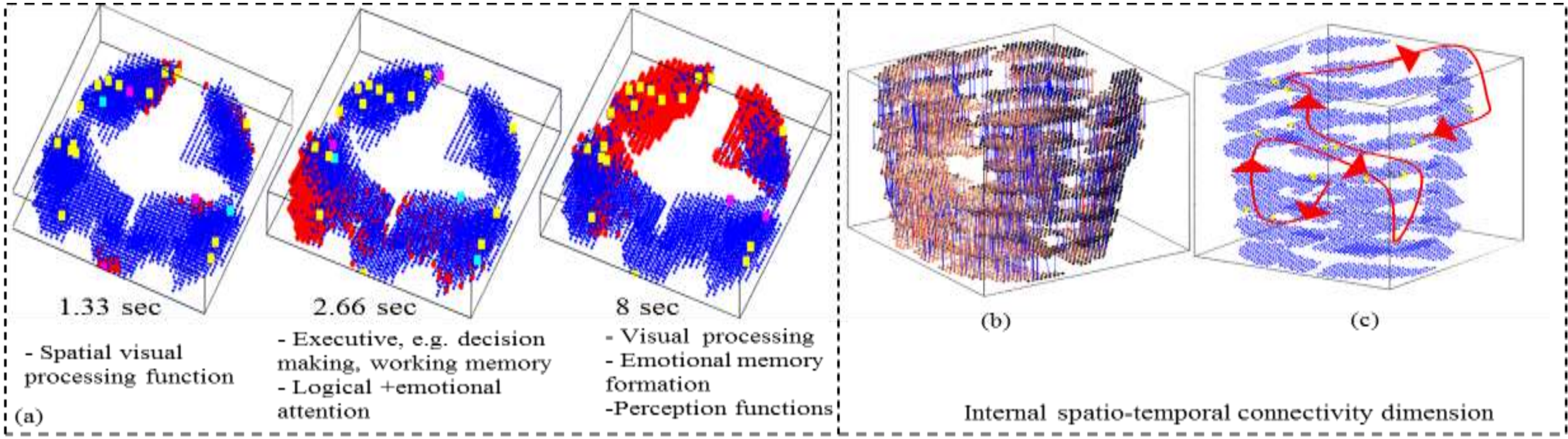
(Spatial mapping of fMRI voxels into a 3D SNN cube after conversion into Talairach coordinates.

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)

NeuCube for learning and knowledge representation of cognitive fMRI STD



Only three snapshots of learning of 8-second fMRI data in a NeuCube model when a subject is reading a negative sentence (time is in seconds) (the left 3 figures); Internal structural pattern represented as spatio-temporal connectivity in the SNN model trained with 8-second fMRI data stream; a functional pattern represented as a sequence of spiking activity of clusters of spiking neurons in a trained NeuCube model (the right most figure).

TSK representation extracted from a trained SNN model related to modelling fMRI data when a person is reading a negative sentence

IF (a person is reading a negative sentence)

THEN (the following events are triggered in space and time in a trained SNN model)

E1: Vision, in the Spatial Visual Processing area, at time T1,

AND E2: Decision making function, in the Decision making and working memory, at time T2,

AND E3: Logical and Emotional Attention function, in the Attentional brain area, at time T3

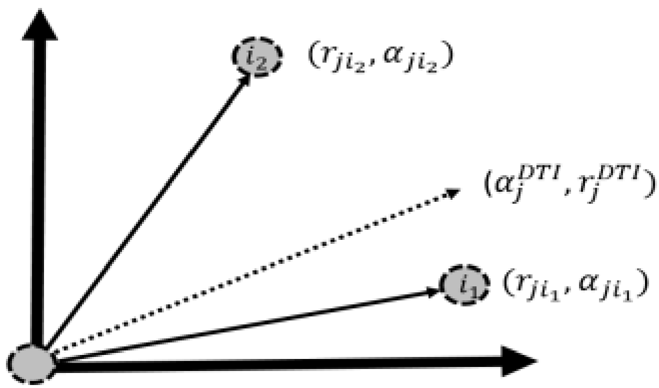
AND E4: Emotional functions, in the Emotional brain area, at time T4

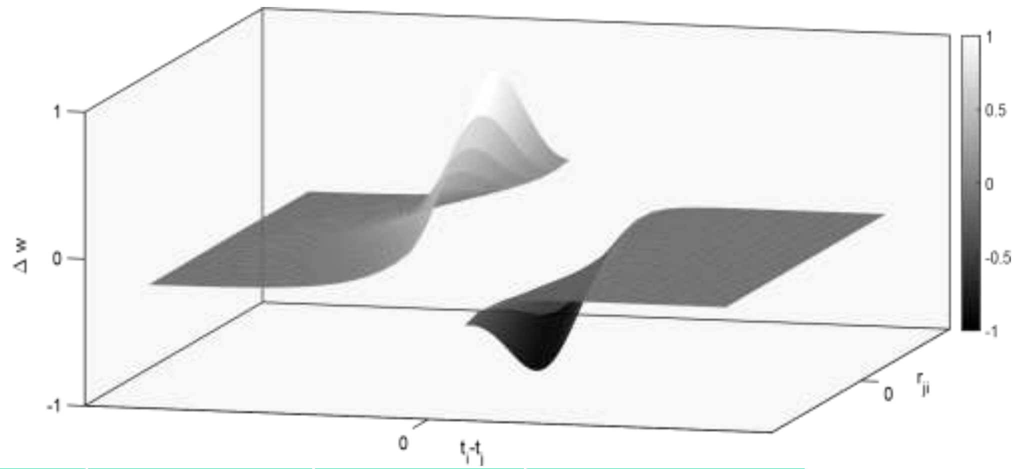
AND E5: Emotional memory formation function, in the Memory brain area, at time T5

AND E6: Perception function, Perception brain area, at time T6.

Deep learning of time-, space- and direction data

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





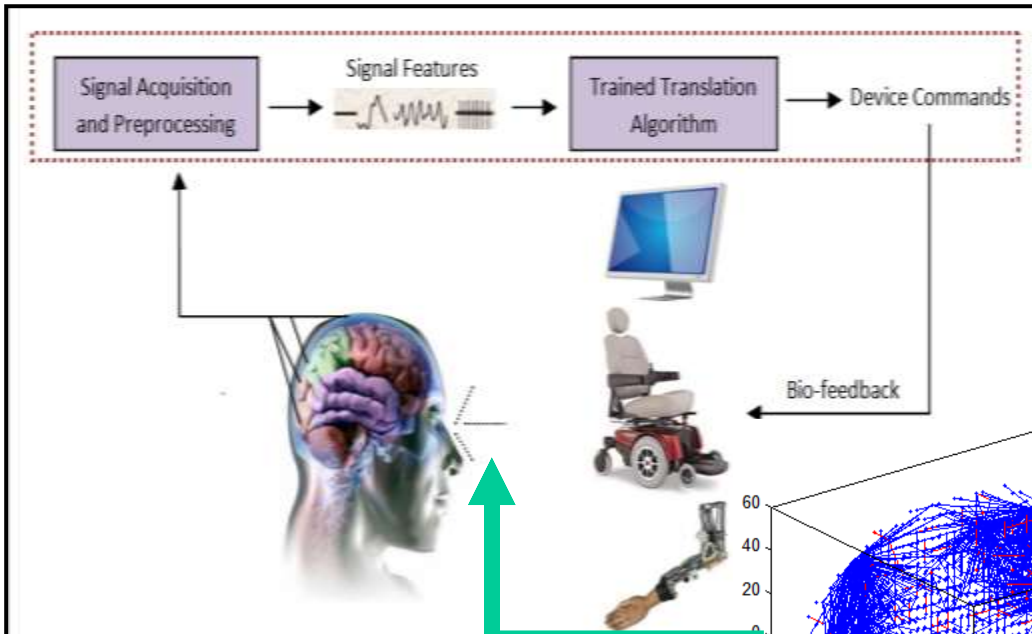
Method	Data	Temporal	Multi-dimensional	Accuracy(%)	Cohen's κ
BSA+oiSTDP+KNN	fMRI+DTI	yes	Yes	**72.3±12.3**	0.44±0.25
BSA+STDP+KNN	fMRI	Yes	no	69.4±13.9	0.38±0.28
BSA+KNN	fMRI	no	No	64.2±12.4	0.22±0.26
Sparse Autoencoder [45]+KNN(E) [44]	fMRI	No	no	56.1±7.2	0.01±0.11
PCA [44]+KNN(E) [44]	fMRI	no	No	56.1±11.3	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

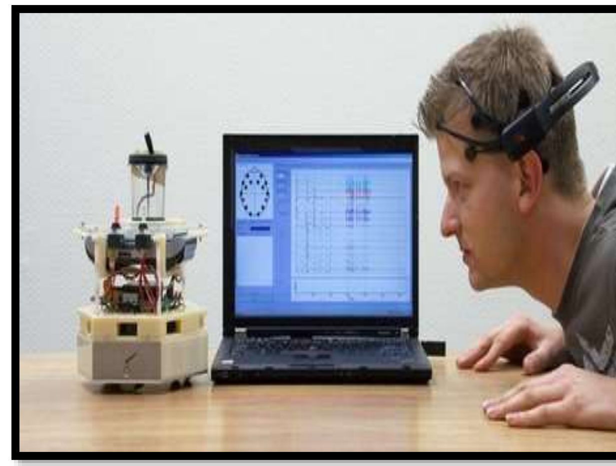
Sengupta, N., McNabb, C. B., Kasabov, N., & Russell, B. R. (2018). Integrating Space, Time, and Orientation in Spiking Neural Networks: A Case Study on Multimodal Brain Data Modelling. IEEE Transactions on Neural Networks and Learning Systems, 29(11). doi:10.1109/TNNLS.2018.2796023

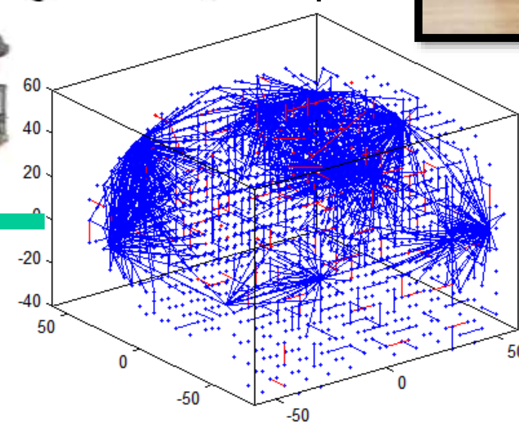
Brain-Inspired Brain Computer Interfaces (BI-BCI)

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.



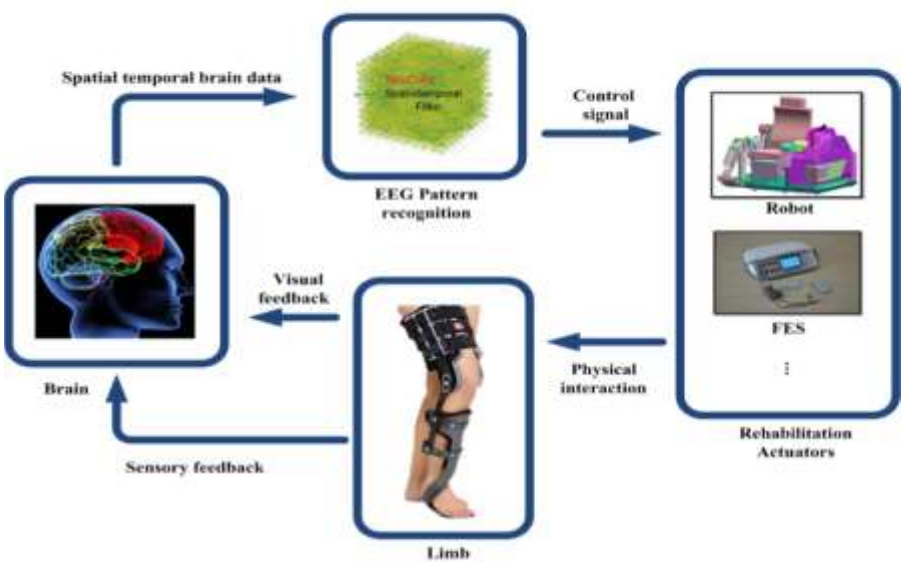


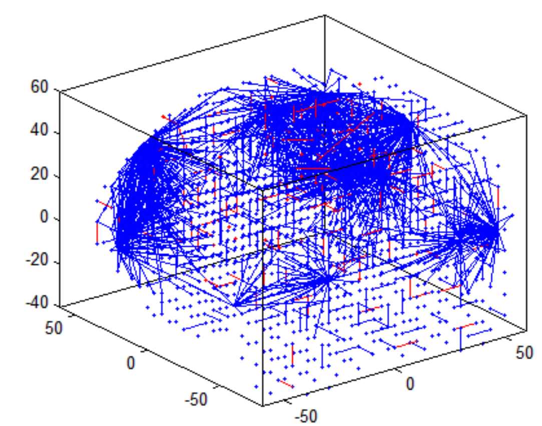


BI-SNN for neurorehabilitation

(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.



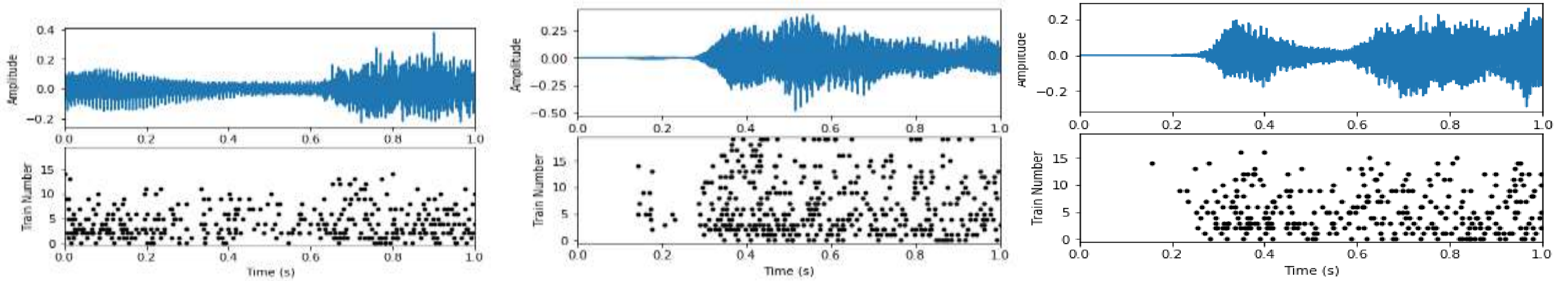


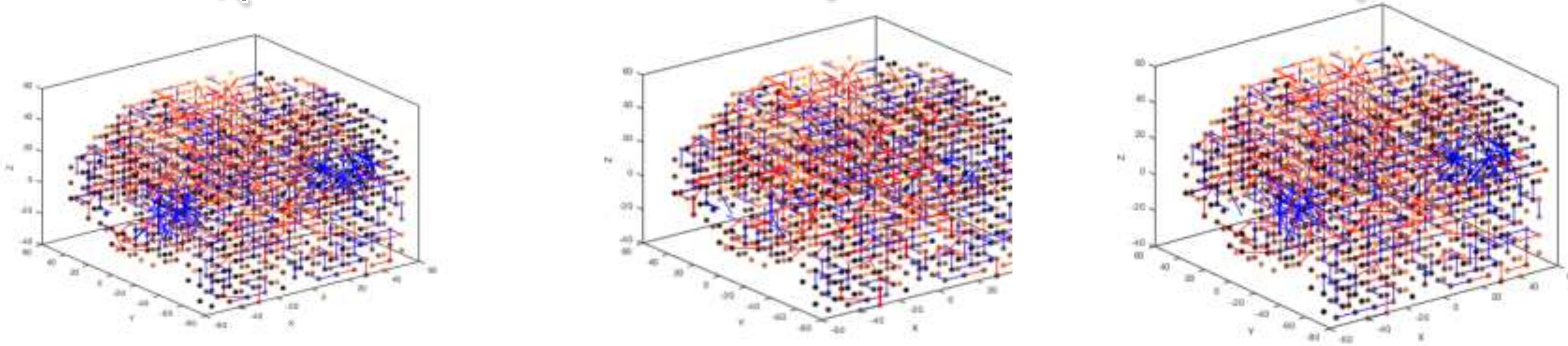
nkasabov@aut.ac.nz

AUT

Deep learning and representation of audio-visual data

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



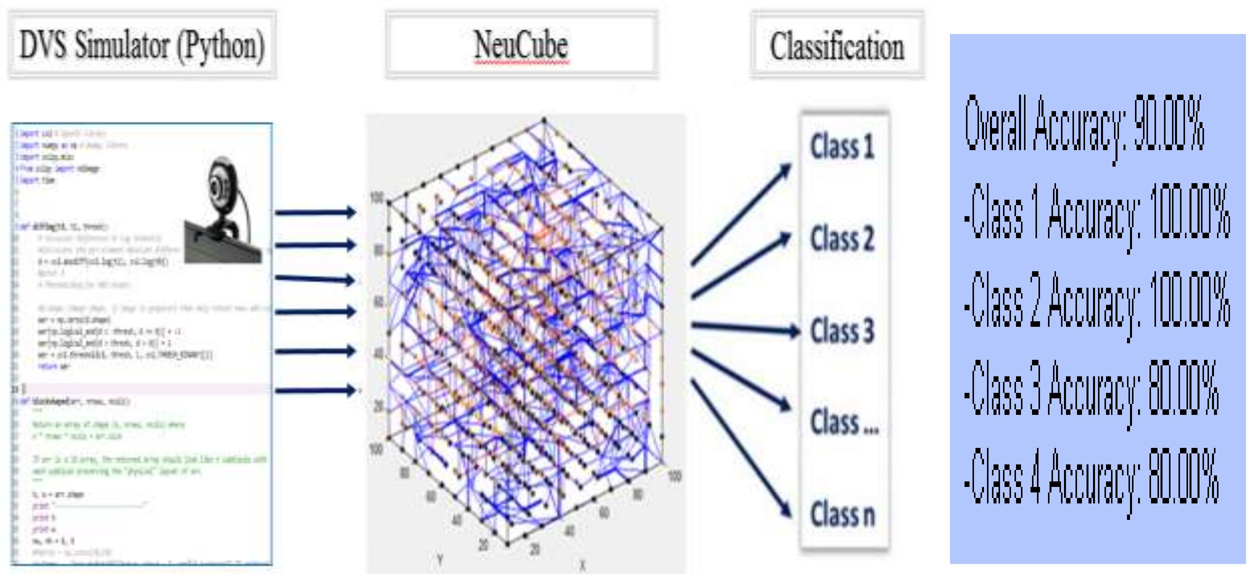


	Mozart	Bach	Vivaldi
Predicted 1	171	3	1
Predicted 2	9	176	1
Predicted 3	0	1	178

BI-SNN for fast object recognition from video streaming data

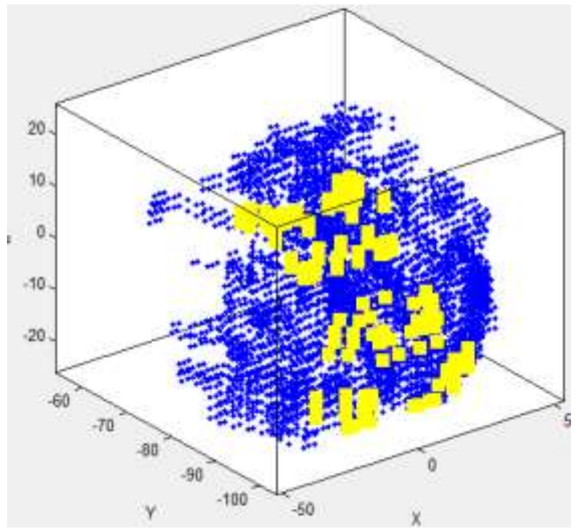
Applications:

- Surveillance systems
- Cybersecurity
- Military applications
- Autonomous vehicles

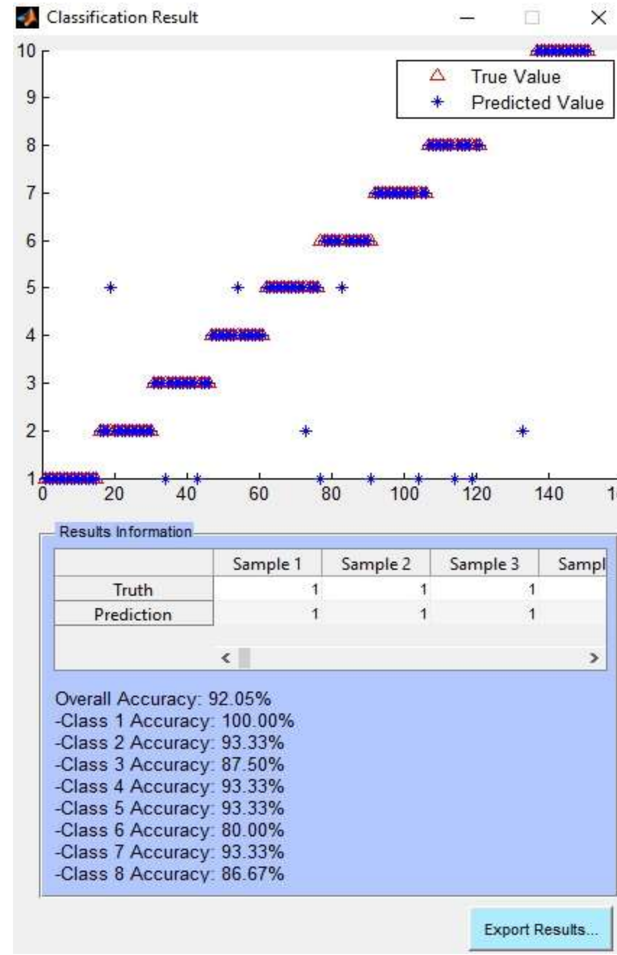


Deep learning and knowledge representation of moving objects using DVS and retinotopic mapping in NeuCube

30000 moving digits in 8 fonts and sizes from DVS MNIST



NeuCube with 4262 neurons from V1 and V2

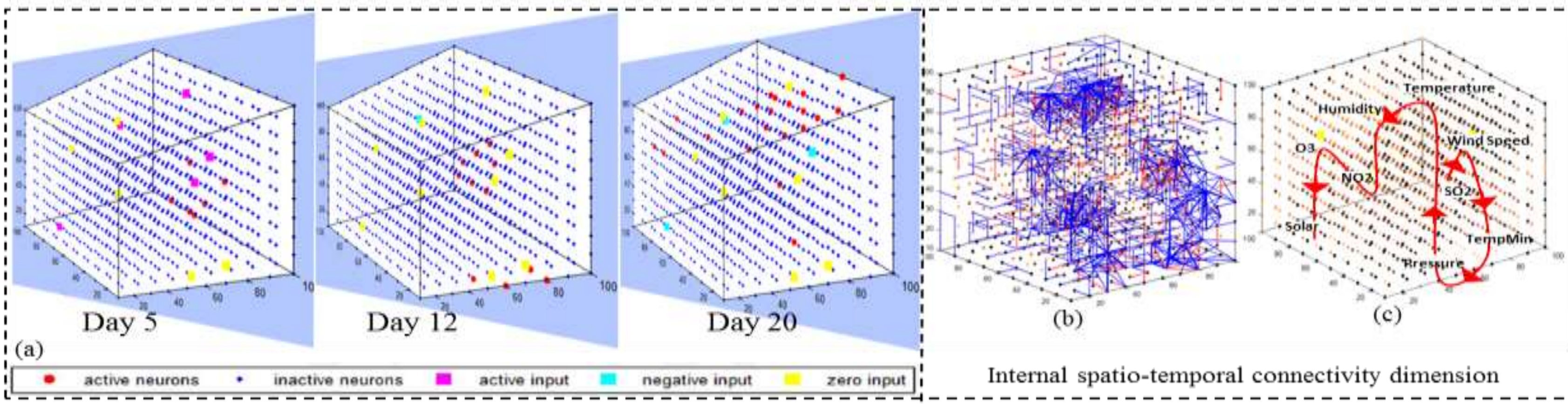


L.Paulin**,** A.Abbott, N.Kasabov, A retinotopic spiking neural network system for accurate recognition of moving objects using NeuCube and dynamic vision sensors, Frontiers of Comp. Neuroscience, 2018, doi:10.3389/fncom.2018.00042.

Predictive modelling of individual stroke occurrence using personal and environmental multisensory TSD

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).

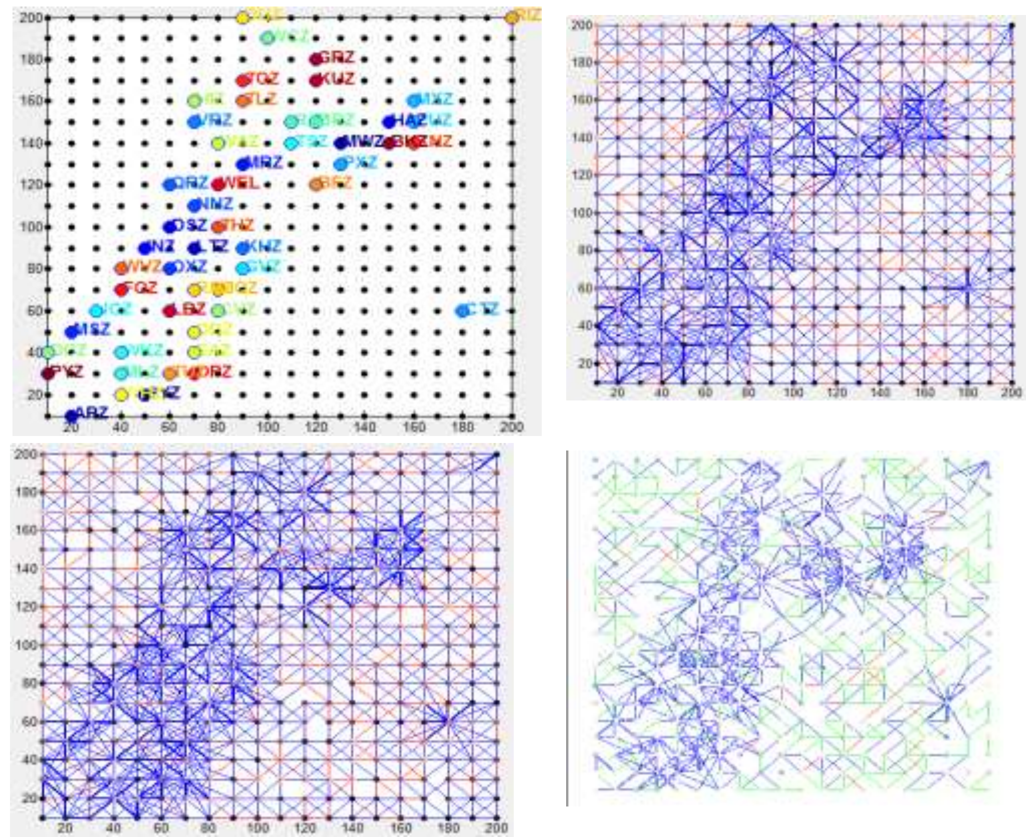


A spatio-temporal rule extracted from a trained SNNcube on climate data relate to a high risk of stroke for a group of individuals

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 TSD 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.

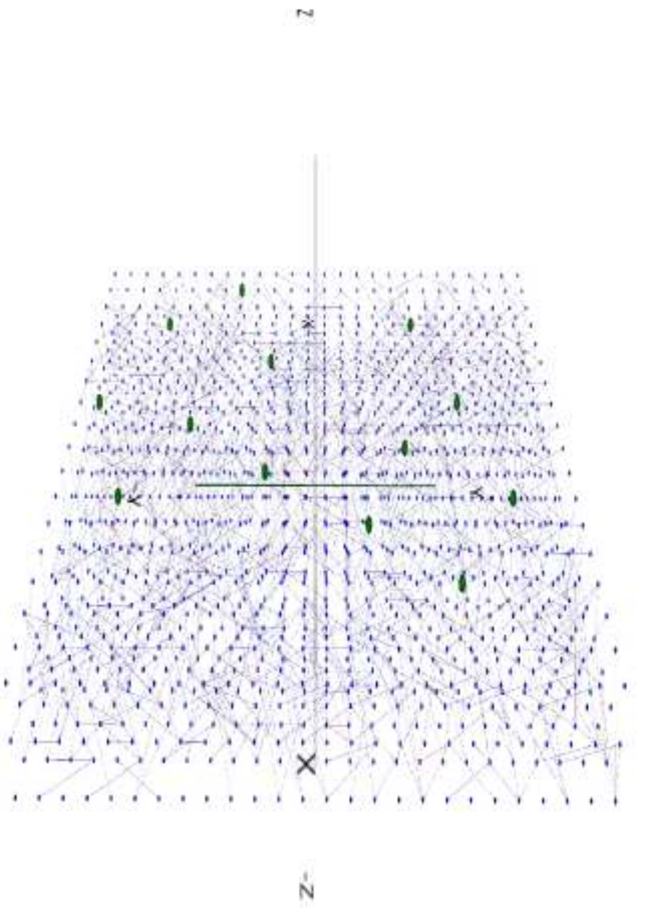


Measure	NeuCube	SVM	MLP
1h ahead	**91.36%**	65%	60%
6h ahead	**83%**	53%	47%
12h ahead	**75%**	43%	46%

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

Wind TSD modelling for energy prediction from wind turbines

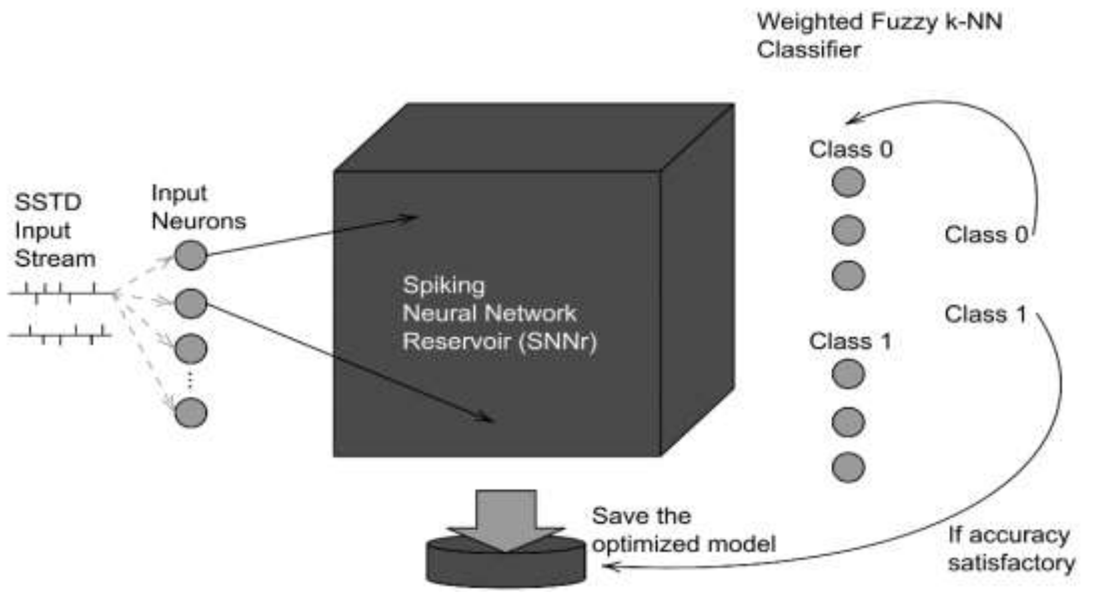
New Zealand

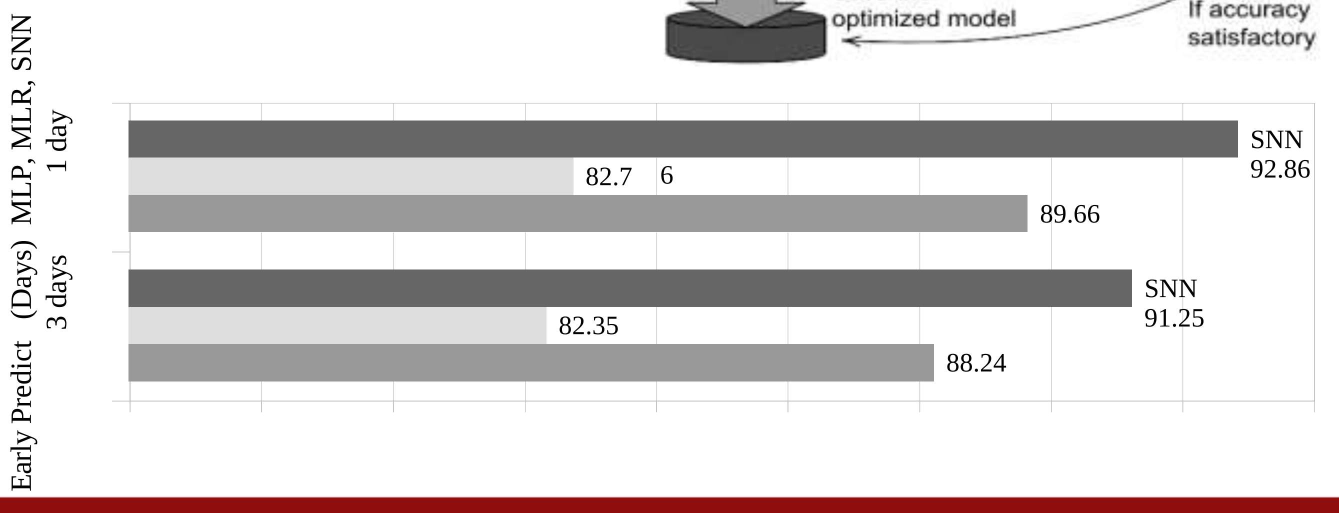


Xinjiang, China (中国新疆）

Flood events risk assessment using environmental TSD

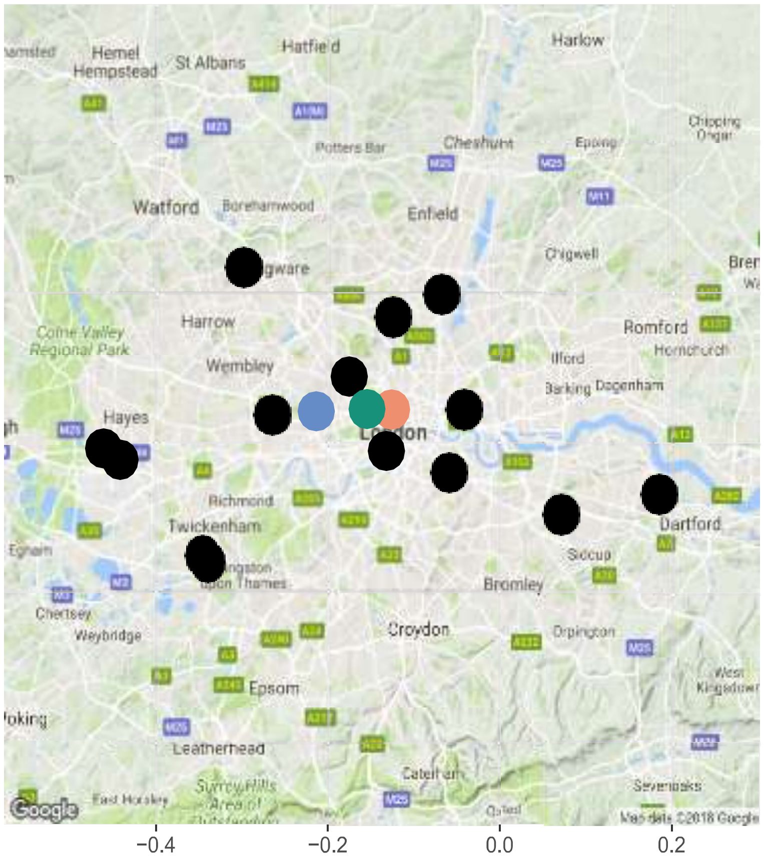
Mohd Hafizul Afifi Abdullah, **Muhaini Othman**, Shahreen Kasim, Siti Aisyah Mohamed, Evolving spiking neural networks methods for classification problem: a case study in flood events risk assessment, Indonesian Journal of Electrical Engineering and Computer Science Vol. 16, No. 1, October 2019, pp.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

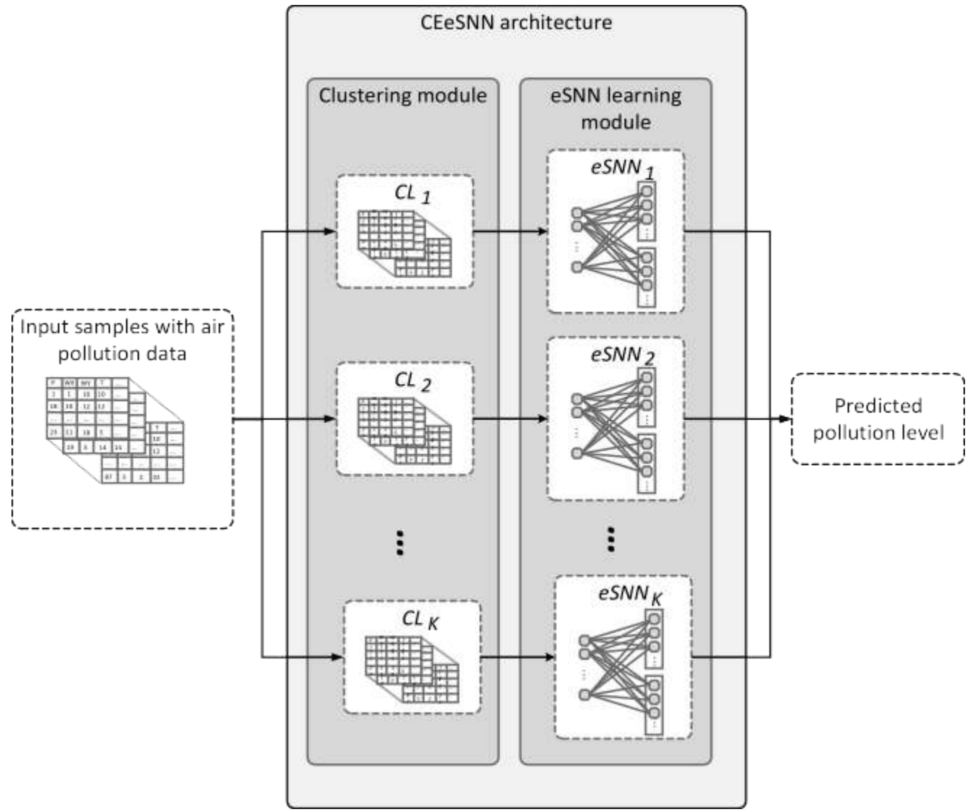




nkasabov@aut.ac.nz

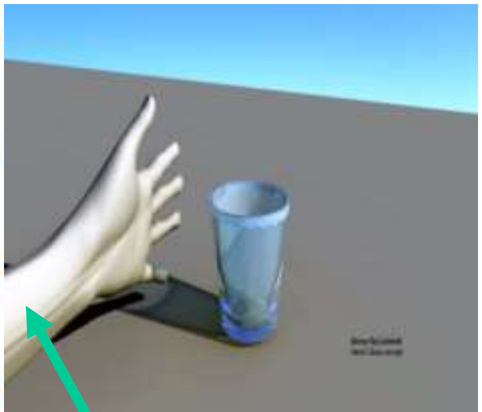
Using an ensemble of eSNN for Predicting Hourly Air Pollution in London Area from sensory TSD

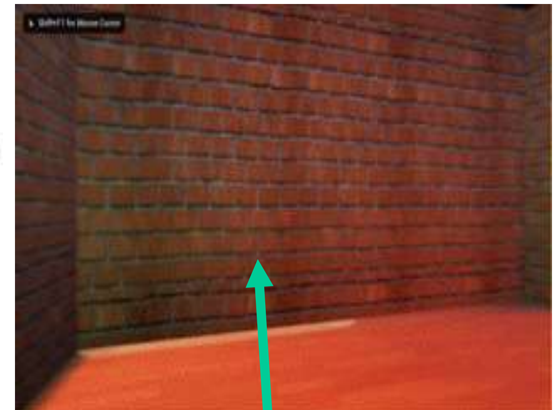




P. S. P Maciaga, N. K. Kasabov, M. Kryszkiewicza, R. Benbenik, Prediction of Hourly Air Pollution in London Area Using Evolving Spiking Neural Networks, Environmental Modelling and Software, Elsevier, vol.118, 262-280, 2019, https://www.sciencedirect.com/science/article/pii/S1364815218307448?dgcid=author

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

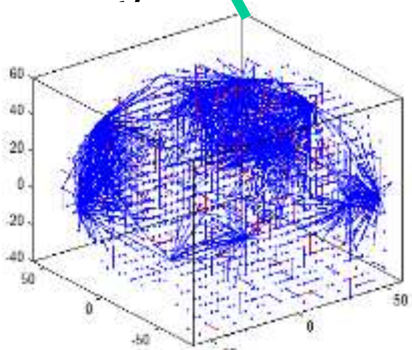


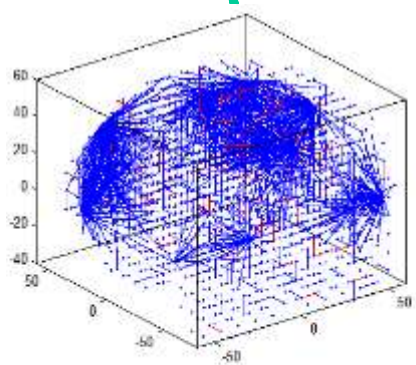


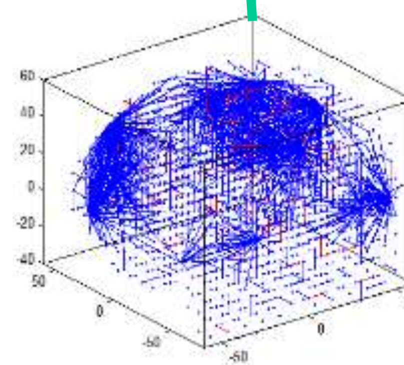
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.

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.



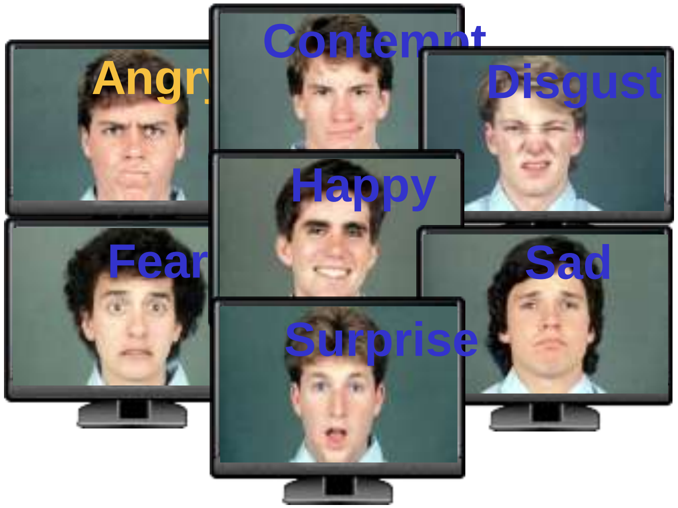




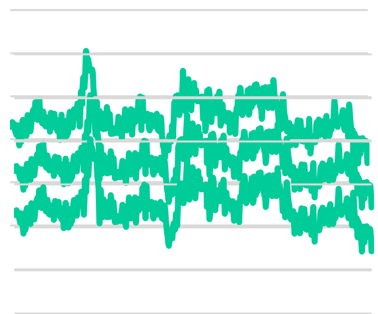
Emotional facial expression recognition and facial expression production

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

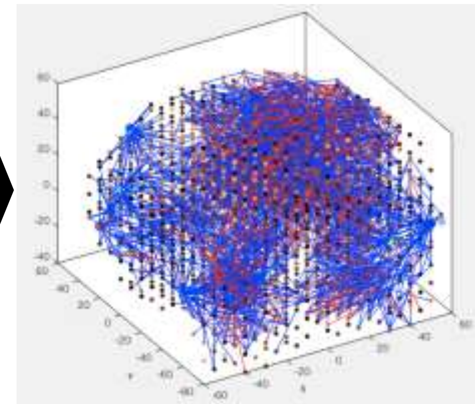
Facial Expression Perception Task



14ch EEG



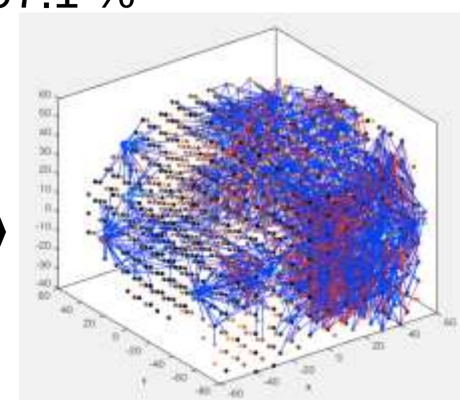
94.3 %



Face Expression Production Task

14ch EEG

97.1 % NeuCube



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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.

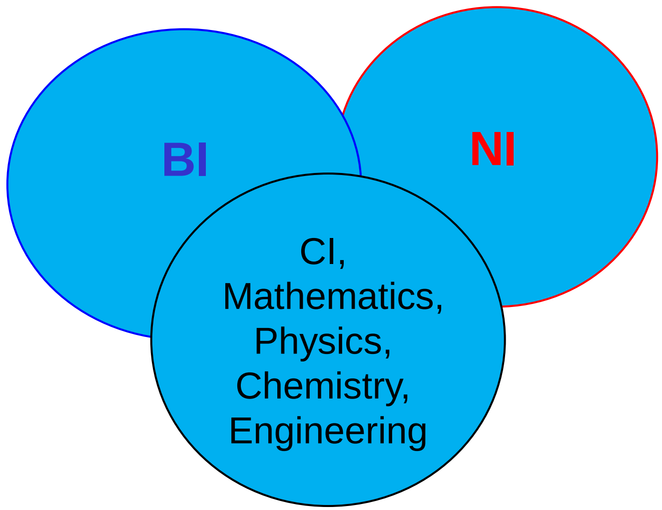
N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019)

nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

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)

Future directions: BI-AI through BI-SNN architectures



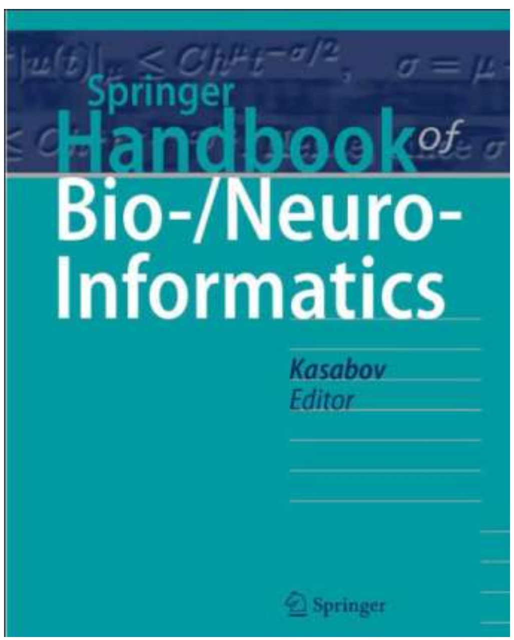
New BI-, and hybrid computational methods and systems

New Data Technologies

Transparent AI

- 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
-

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

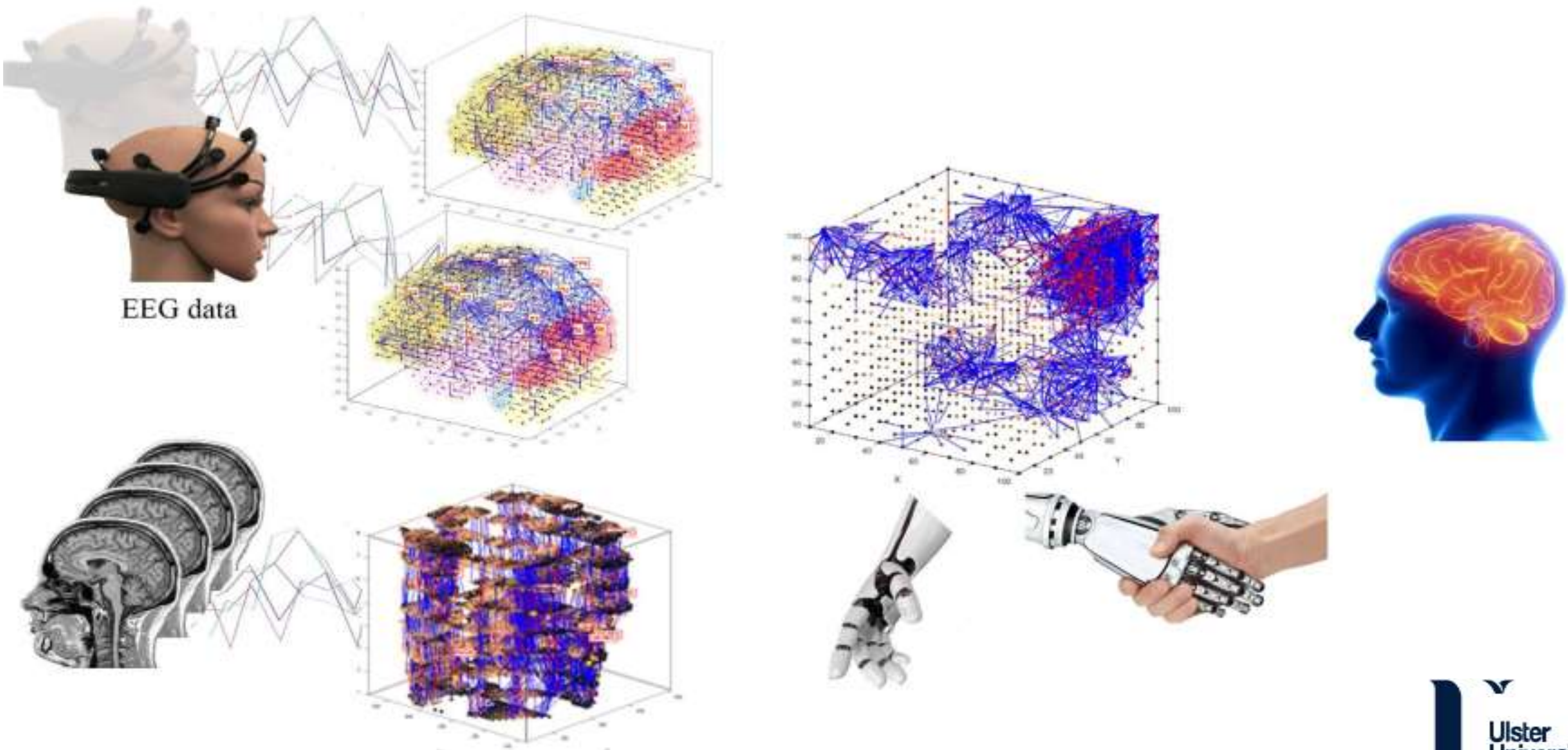


nkasabov@aut.ac.nz nk.kasabov@ulster.ac.uk

Towards Time-Space Knowledge Transfer Between Humans and Machines

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

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



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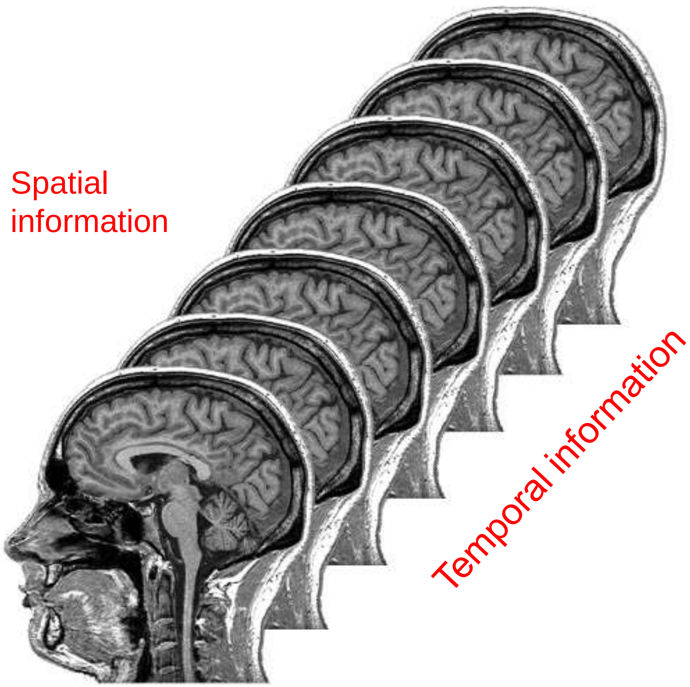
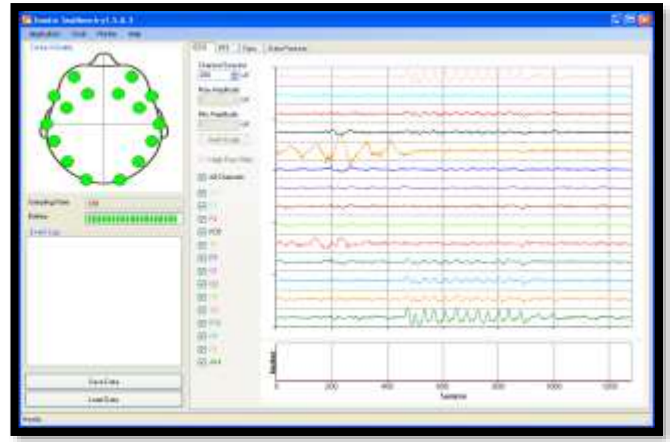
Integrating various TSD, e.g. fMRI and EEG

Spatial
information





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

International BI-SNN Community is growing

Thank you and Questions?

nkasabov@aut.ac.nz   nk.kasabov@ulster.ac.uk   www.academics.aut.ac.nz/nkasabov