Spiking Neural Networks: The Machine Learning Approach

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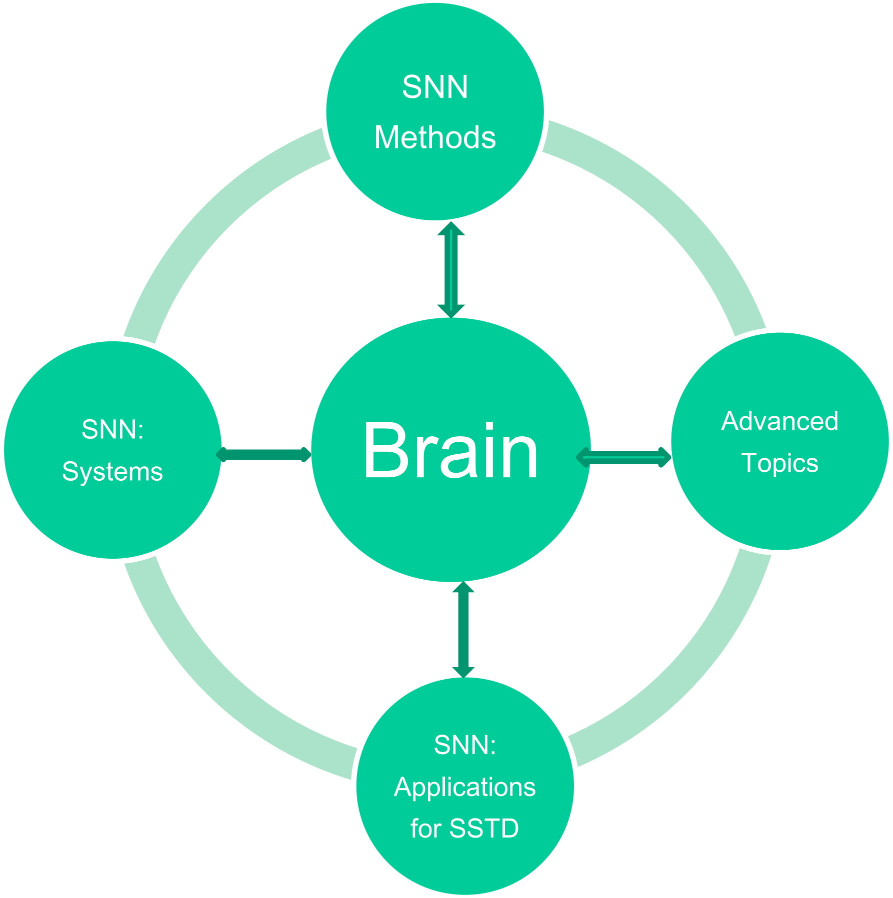
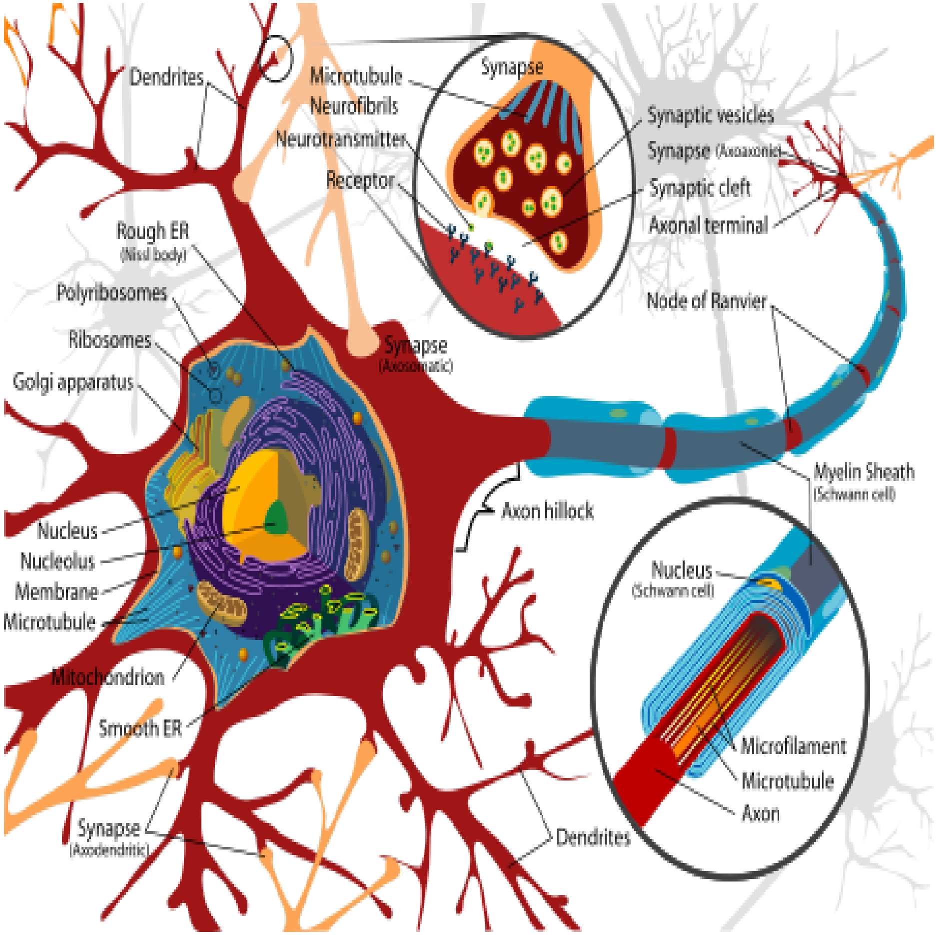


Content

Part I: SNN Methods

1. Biological motivation for neurocomputation



A single neuron is very rich of information processes: time; frequency; phase; field potentials; molecular (genetic) information; space.

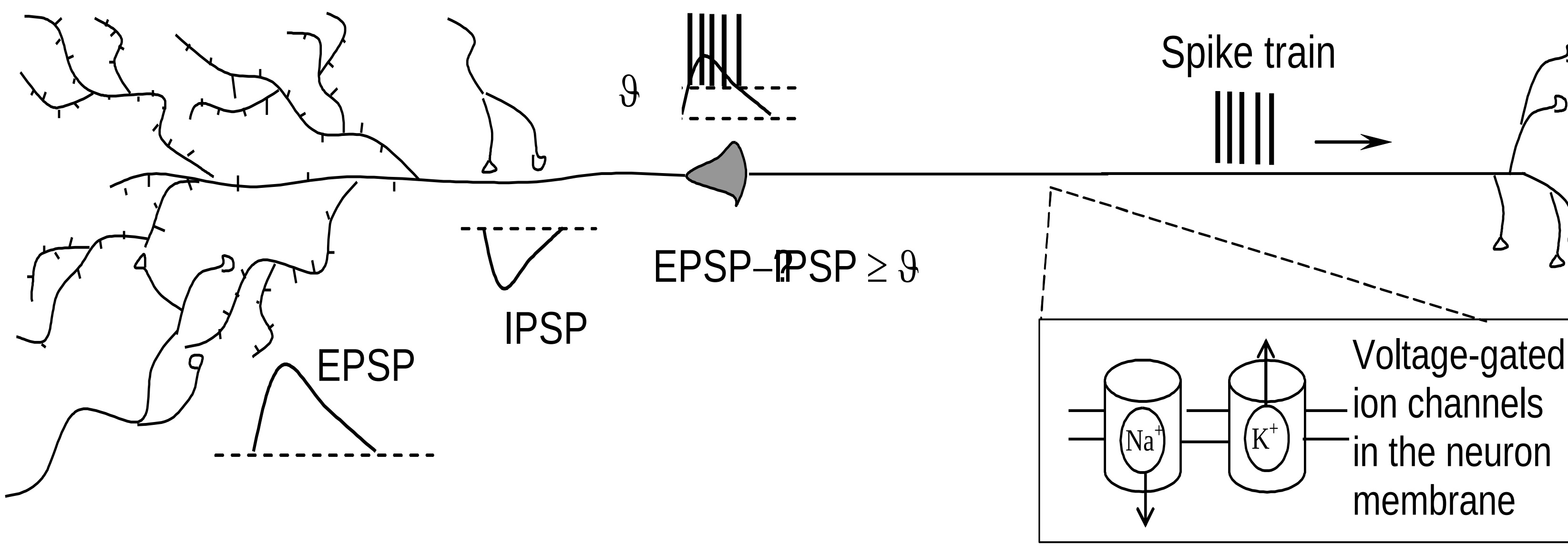
Three, mutually interacting, memory types

- short term;
- long term
- genetic

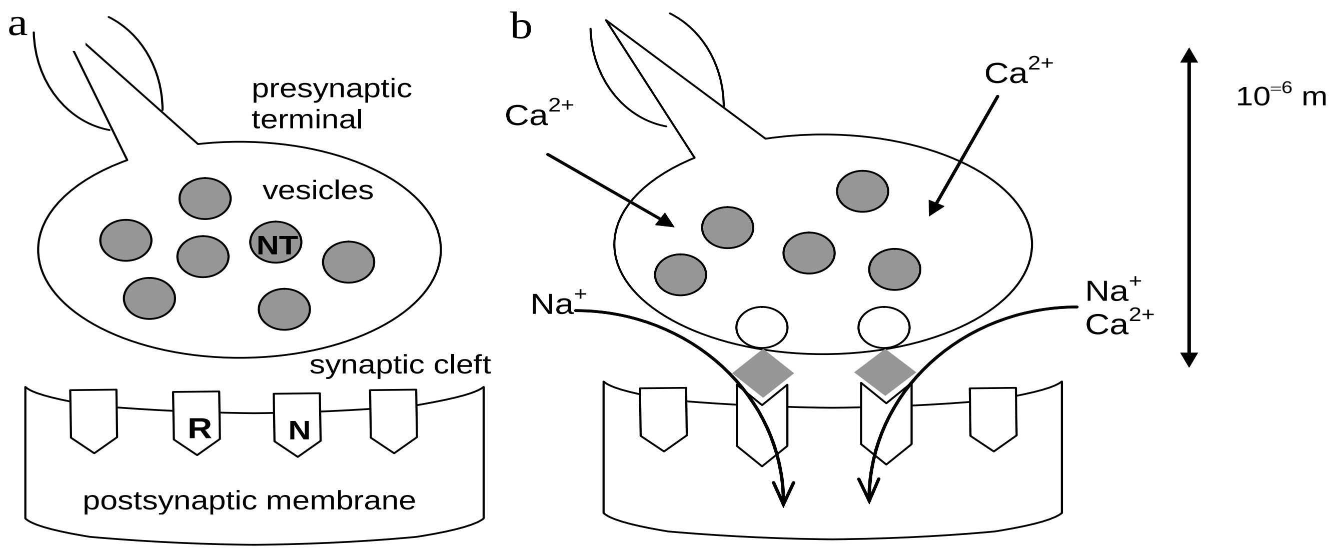
SNN can accommodate both spatial and temporal information as location of neurons/synapses and their spiking activity over time.

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.



How does a synapse work?



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. Spiking neuron models

Information processing principles in SNN:

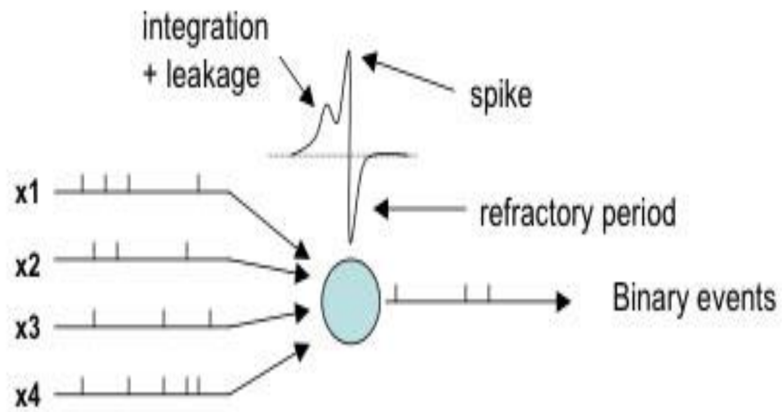
- LTP and LTD
- Trains of spikes
- Time, frequency and space
- Synchronisation and stochasticity
- Evolvability…

Models of a spiking neuron and SNN

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

They offer the potential for:

- Bridging neuronal functions and “lower” level genetics
- Bridging spiking activities with quantum properties
- Integration of modalities
- Temporal or spatio-temporal data modelling

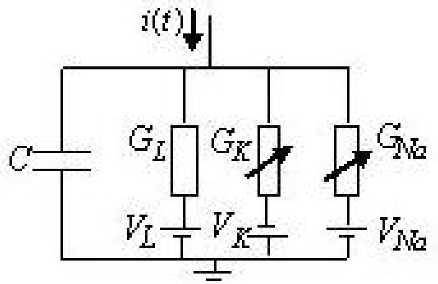


… Models of Spiking Neurons

- Spiking neurons represent the 3rd generation of neural models, incorporating the concepts of *space* and *time* trough neural connectivity and plasticity
- Neural modeling can be described at several levels of abstraction
- **Microscopic Level:** Modeling of ion channels, that depend on presence/absence of various chemical messenger molecules
  - Hodgkin-Huxley Model
  - Izhikevich model
  - Compartment models describe small segments of a neuron separately by a set of ionic equations
- **Macroscopic Level:** A neuron is a homogenous unit, receiving and emitting spikes according to defined internal dynamics
  - Integrate-and-Fire models
  - Probabilistic 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



$$\sum_{ch} i_{ch}(t) = G_{Na} \times m^3 \times h \times (v_C - V_{Na}) +$$
$$G_K \times n^4 \times (v_C - V_K) + G_L \times (v_C - V_L)$$

$$\frac{dm}{dt} = \alpha_m(v_c) \times (1-m) - \beta_m(v_c) \times m$$

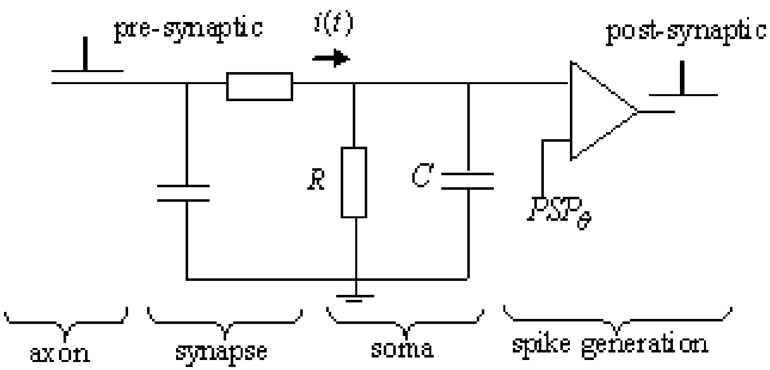
$$\frac{dn}{dt} = \alpha_n(v_c) \times (1-n) - \beta_n(v_c) \times n$$

$$\frac{dh}{dt} = \alpha_h(v_c) \times (1-h) - \beta_h(v_c) \times h$$

- 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 $I(t) = I_R + I_{cap}$



Standard form of the model:

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

- $\tau_m = RC$ 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}

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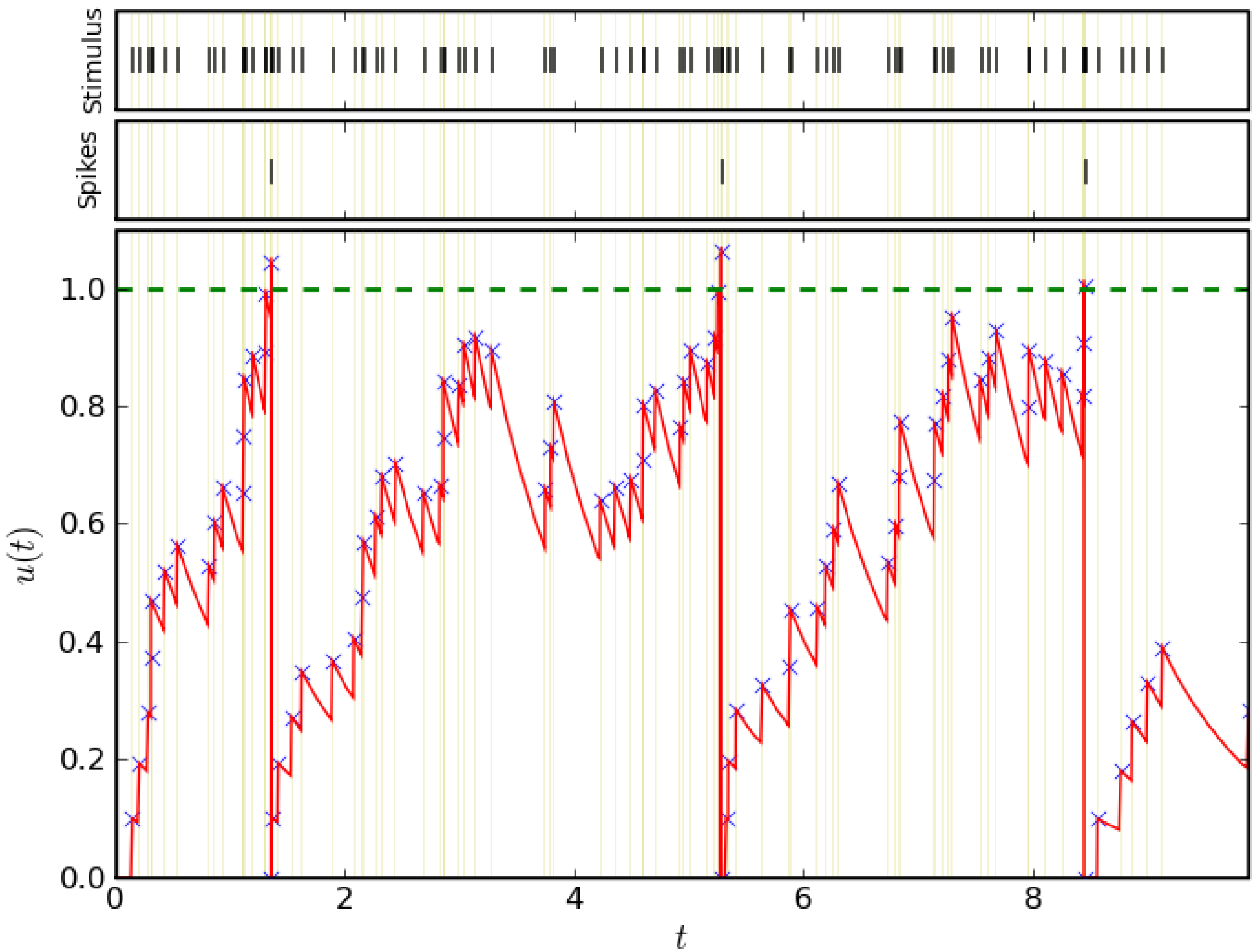
Dynamics of the LIF neuron



Neural Model by Izhikevich

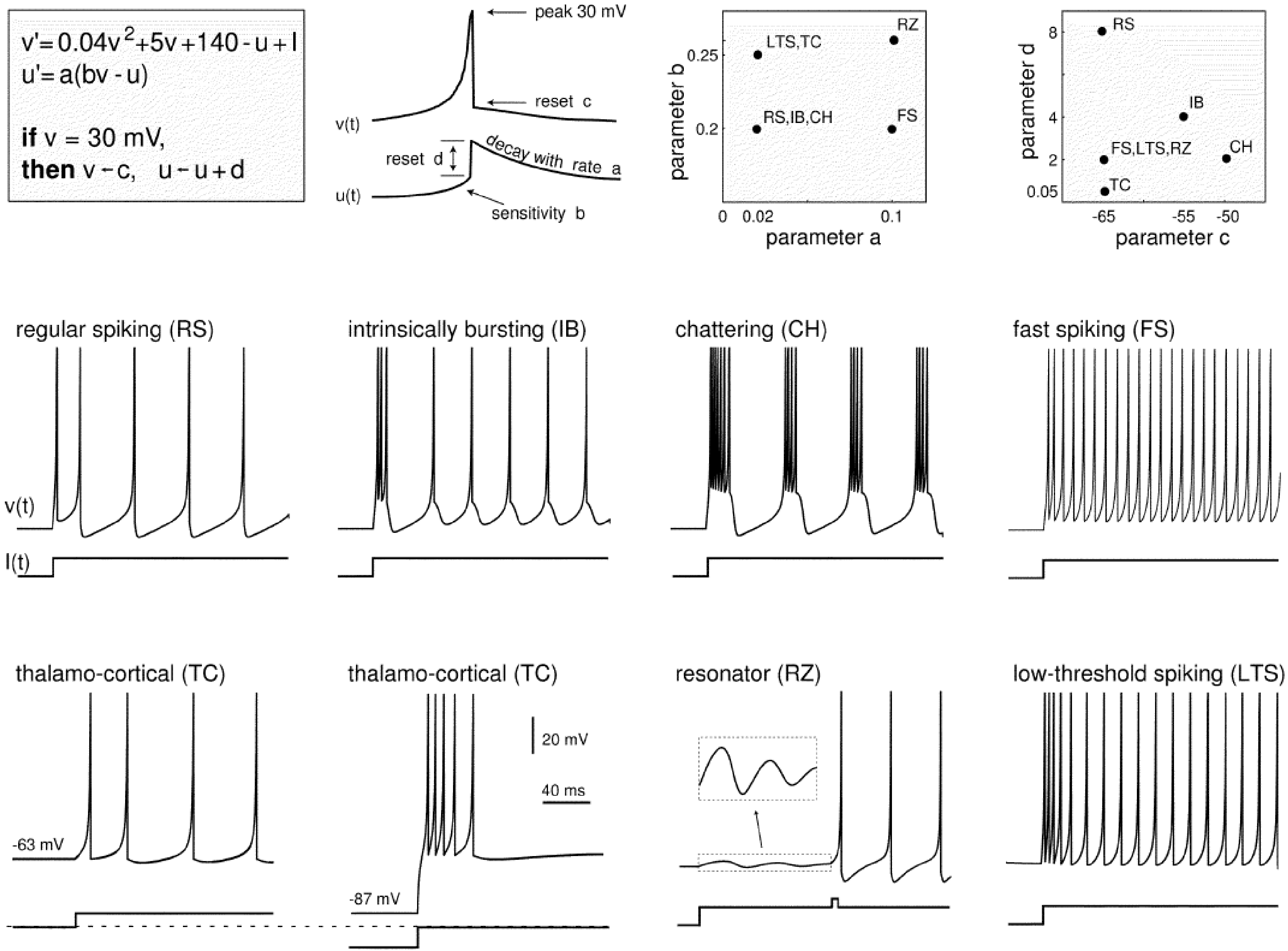
- Model claims to be as biological plausible as the HH model with computational efficiency of LIF models
- Depending on its parameter configuration the model reproduces different spiking and bursting behavior of cortical neurons

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

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

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

Dynamics of the Izhikevich Model



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Spike Response Model

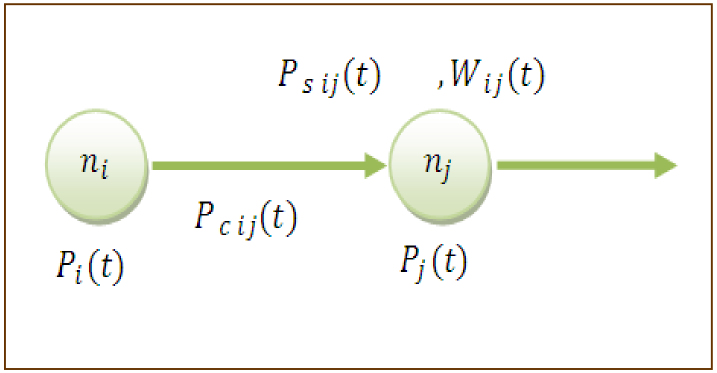
- Generalization of the LIF model, introduced by Gerstner et. al. in 1993
- State of a neuron described by a single variable *u*
- Incoming spikes perturb *u*, which is modeled by a kernel function **ε**
- If *u* reaches a threshold value ϑ, a spike is triggered
- Shape of an action potential and the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

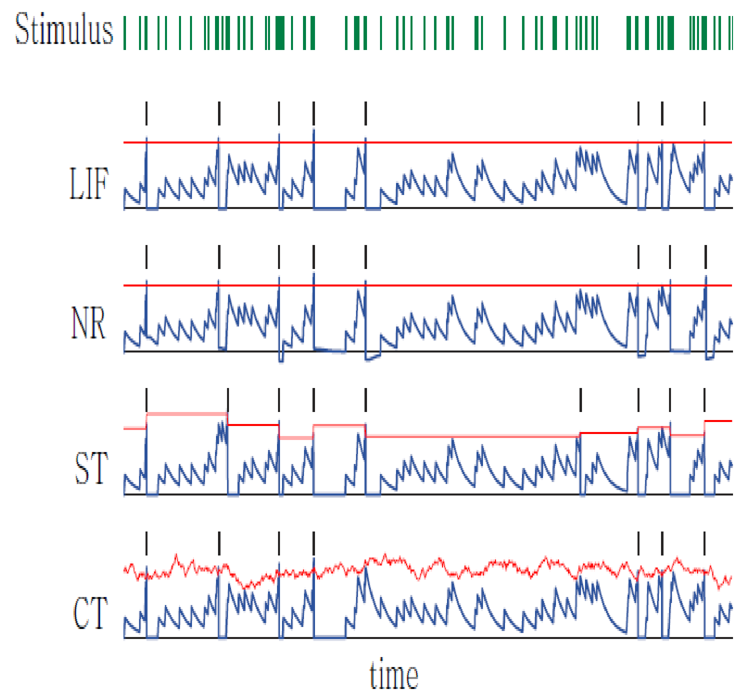
$$u_i(t) = \eta(t - \hat{t}_i) + \sum_j w_{ij} \sum_f \varepsilon_{ij}(t - \hat{t}_i, t - t_j^{(f)})$$

- $t_j^{(f)}$ 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

(Kasabov, 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.

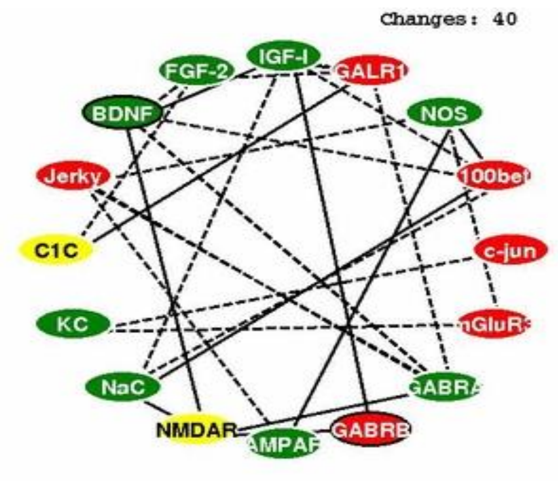
A neurogenetic model of a spiking neuron

(Kasabov, Benuskova, Wysoski, 2005)

- Four types of synapses: fast excitation; slow_excitation; fast_inhibition; slow_inhibition
- A Gene Regulatory Network (GRN) as a dynamical parameter system of the neuron

Table. Neuronal Parameters and Related Proteins

Neuronal parameter Amplitude and time constants of	Protein
Fast excitation PSP	AMPAR
Slow excitation PSP	NMDAR
Fast inhibition PSP	GABRA
Slow inhibition PSP	GABRB
Firing threshold	SCN, KCN, CLC
Late excitatory PSP through GABRA	PV



$$PSP_{ij}^{type}(t-t_j-\Delta_{ij}^{ax}) = A^{type}\left(\exp\left(-\frac{t-t_j-\Delta_{ij}^{ax}}{\tau_{decay}^{type}}\right)-\exp\left(-\frac{t-t_j-\Delta_{ij}^{ax}}{\tau_{rise}^{type}}\right)\right)$$

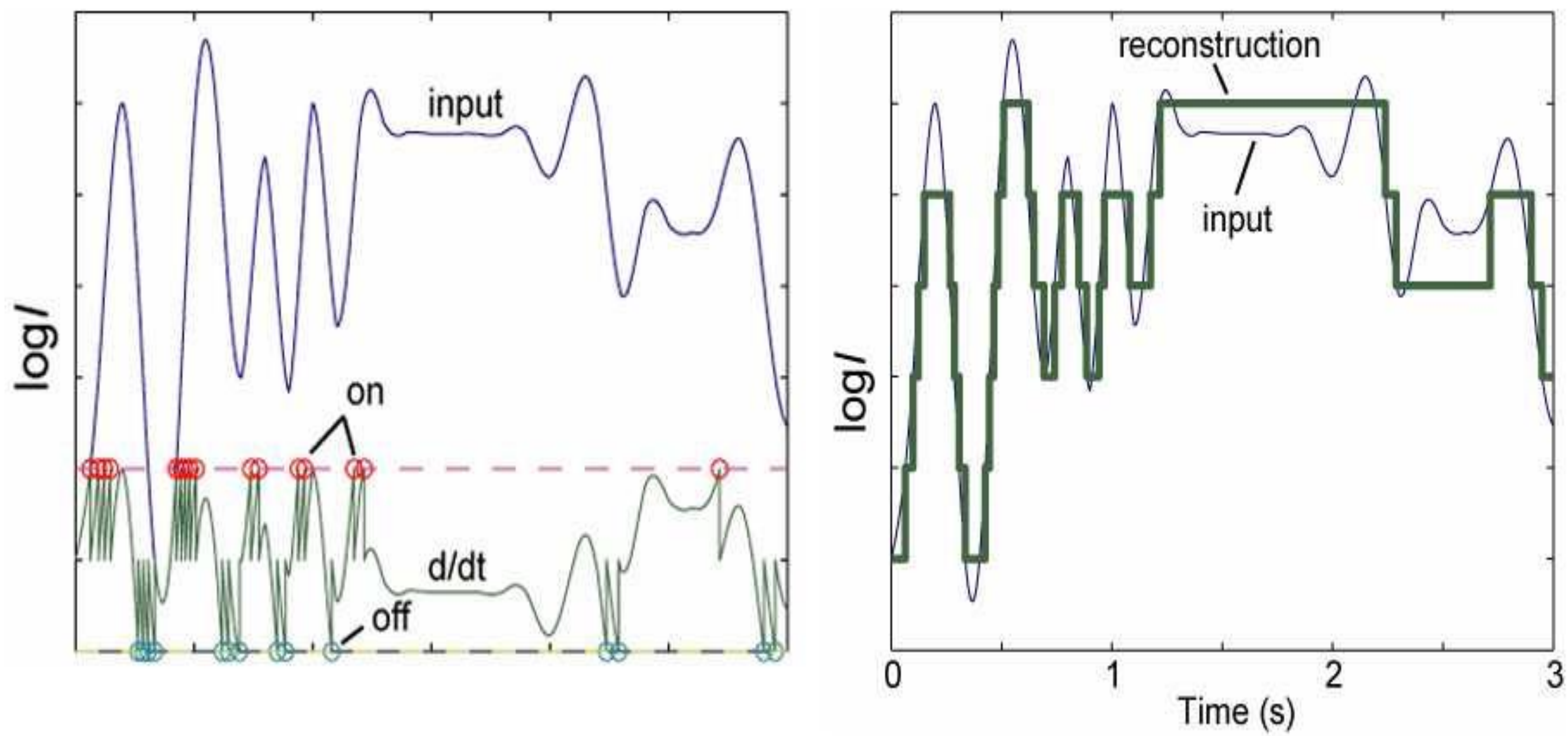
type = fast excitation; slow_excitation; fast_inhibition; slow_inhibition

3. Data and information representation as spikes

Threshold-based encoding (TBE): 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

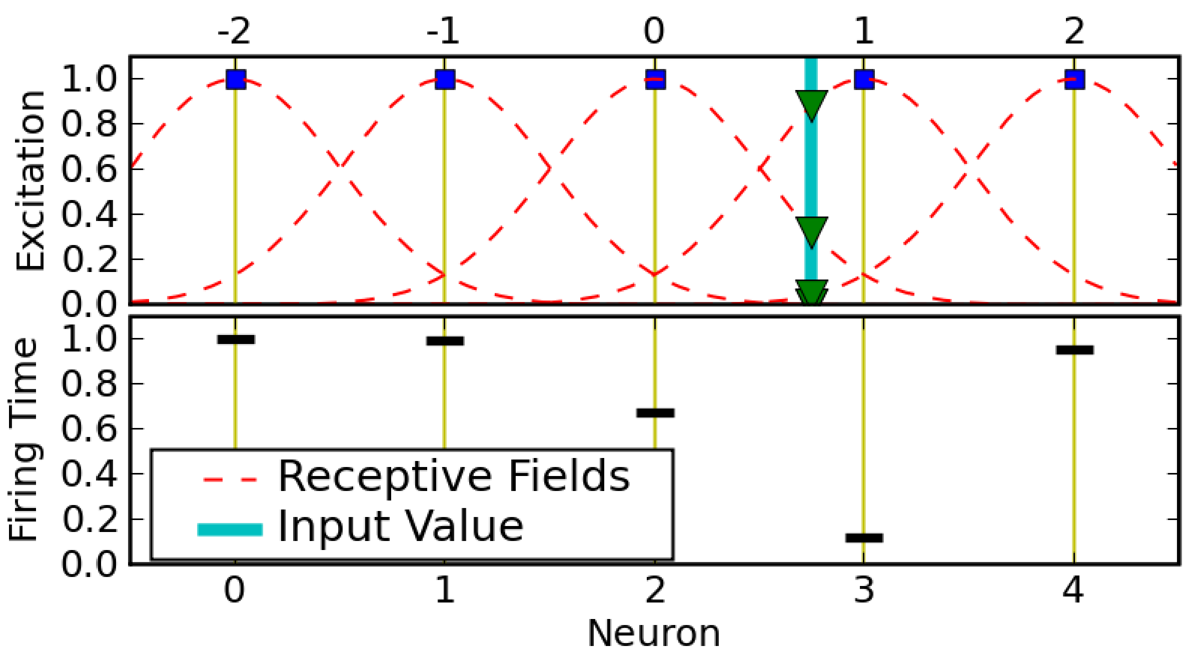
Silicon Cochlea (Shih-Chii Liu, INI, ETH/UZH, Zurich)



… Encoding data into spikes

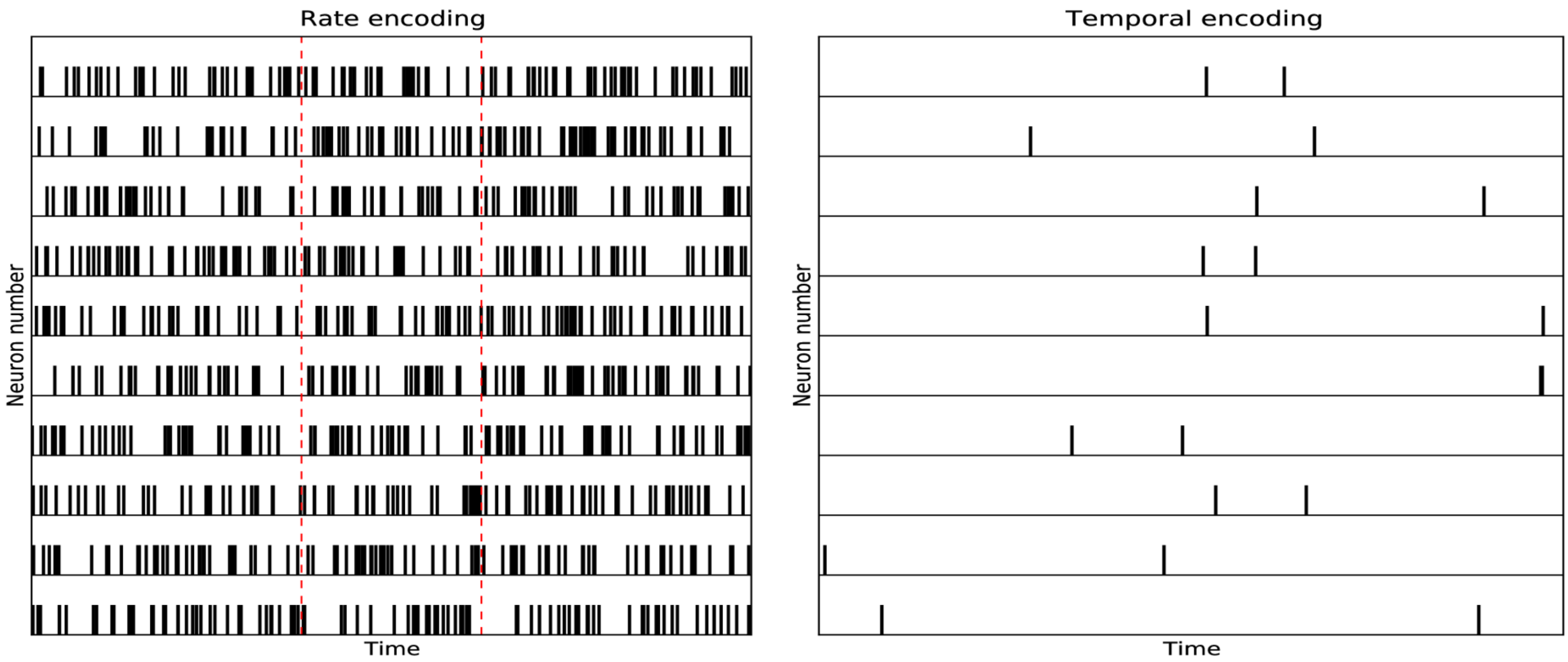
Rank Order Population Encoding

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



Representing information as spikes: Rate vs time-based

- 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! For example: class A is a spike at time 10 ms, class B is a spike at time 20 ms.



4. **Methods for learning in SNN**

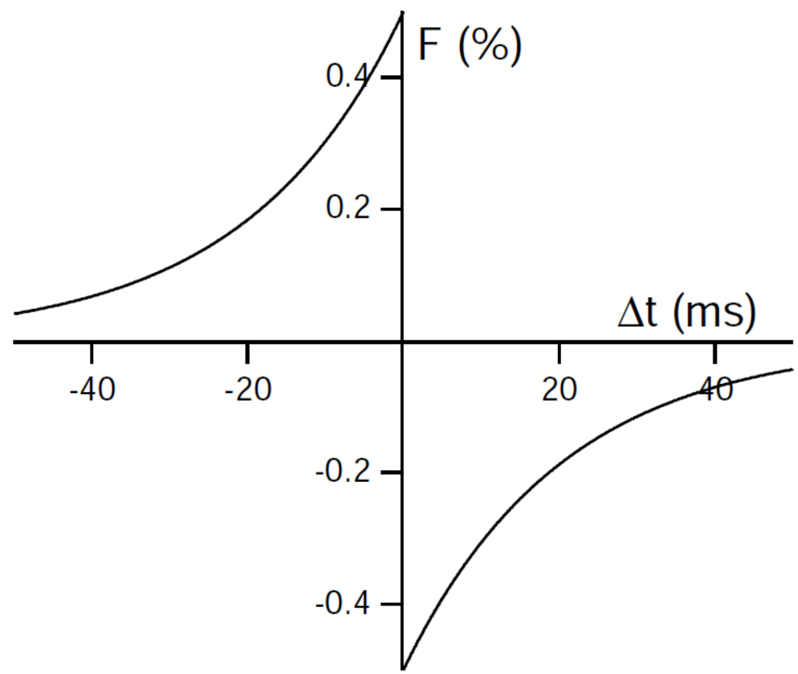
Spike-Time Dependent Plasticity (STDP)

(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.

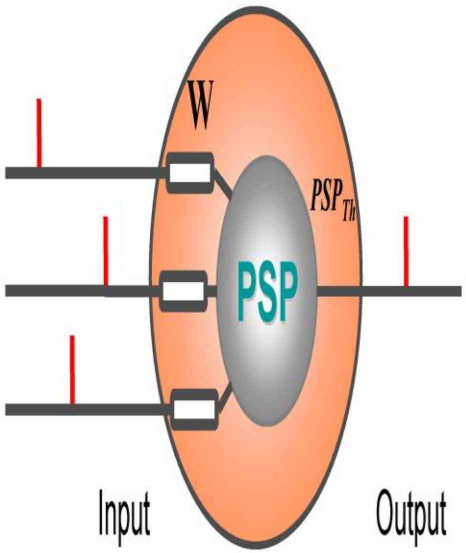
Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD

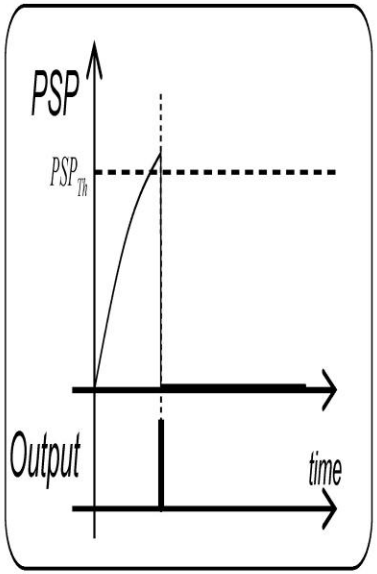
Δt=tpre -tpost



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

PSP_{Th}=C. PSPmax

- Earlier coming spikes (information) are more important
- Predictive spiking, 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)*

- Combine: (a) RO learning for weight initialisation based on2013. the first spikes:

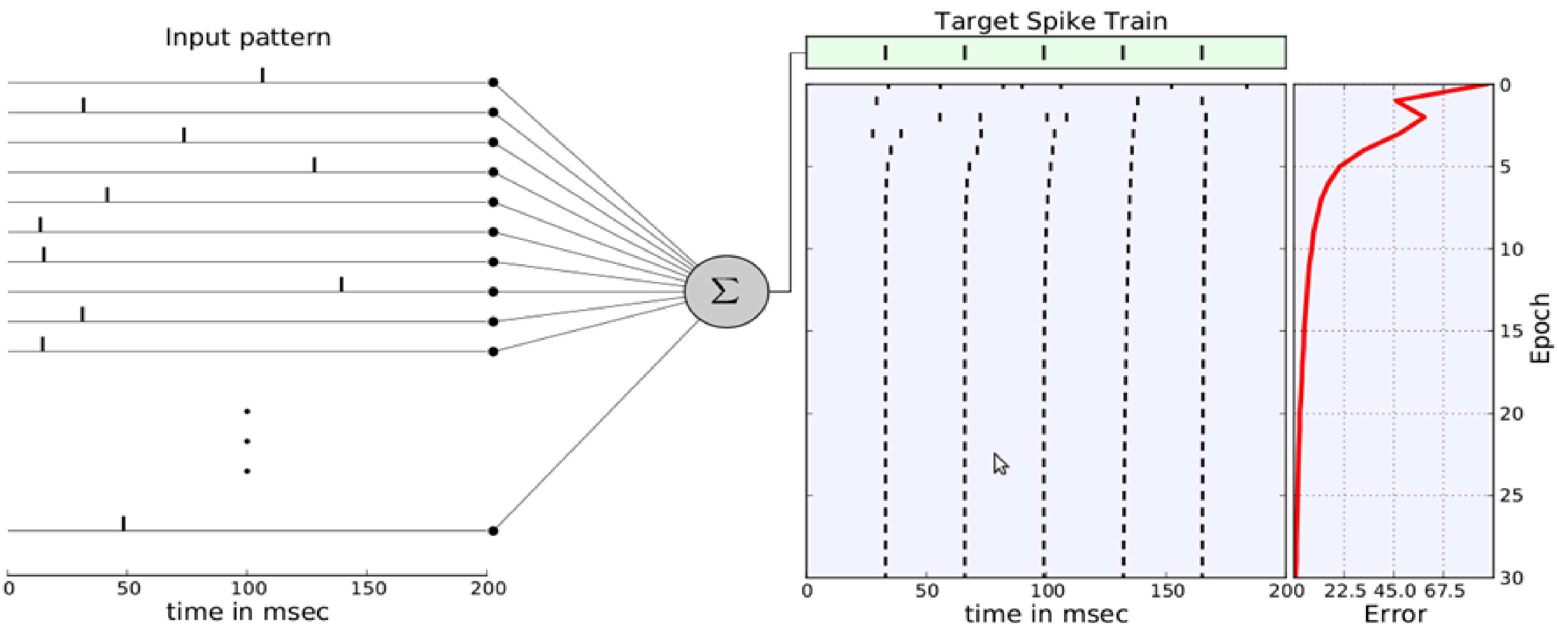
$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

(b) STDP for learning further input spikes at a synapse.

- A new output neuron is added to a respective output repository for every new -input pattern learned.
- Neurons may merge.
- Two types:
  - deSNNm (spiking is based on the membrane potential)
  - deSNNs (spiking is based on synaptic similarity)

Spike Pattern Association Neurons: SPAN

(Mohemmed, A., Schliebs, S., Matsuda, S., & Kasabov, N. (2013). Training spiking neural networks to associate spatio-temporal input-output spike patterns. Neurocomputing, 107, 3-10. doi:10.1016/j.neucom.2012.08.034)



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

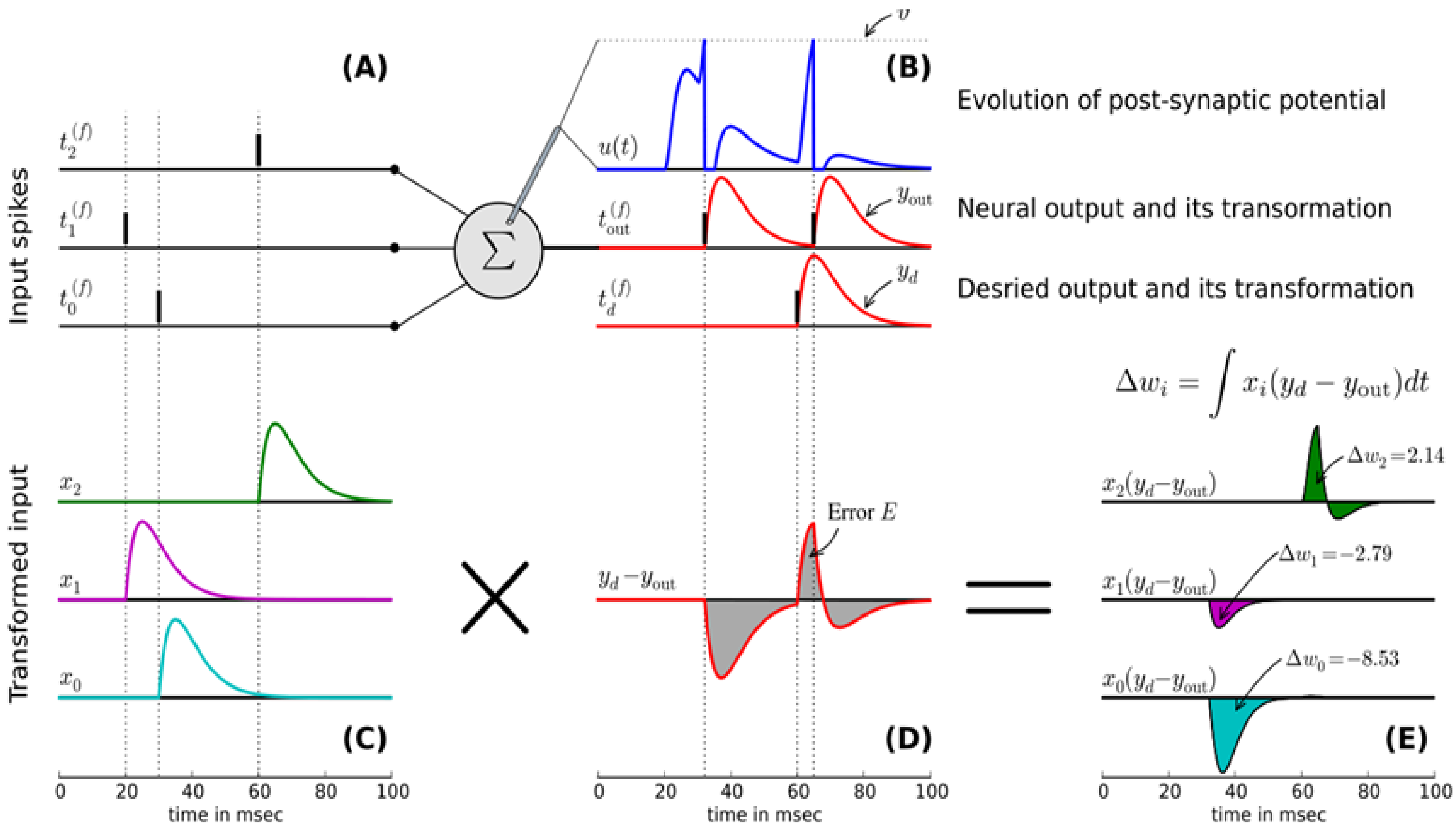
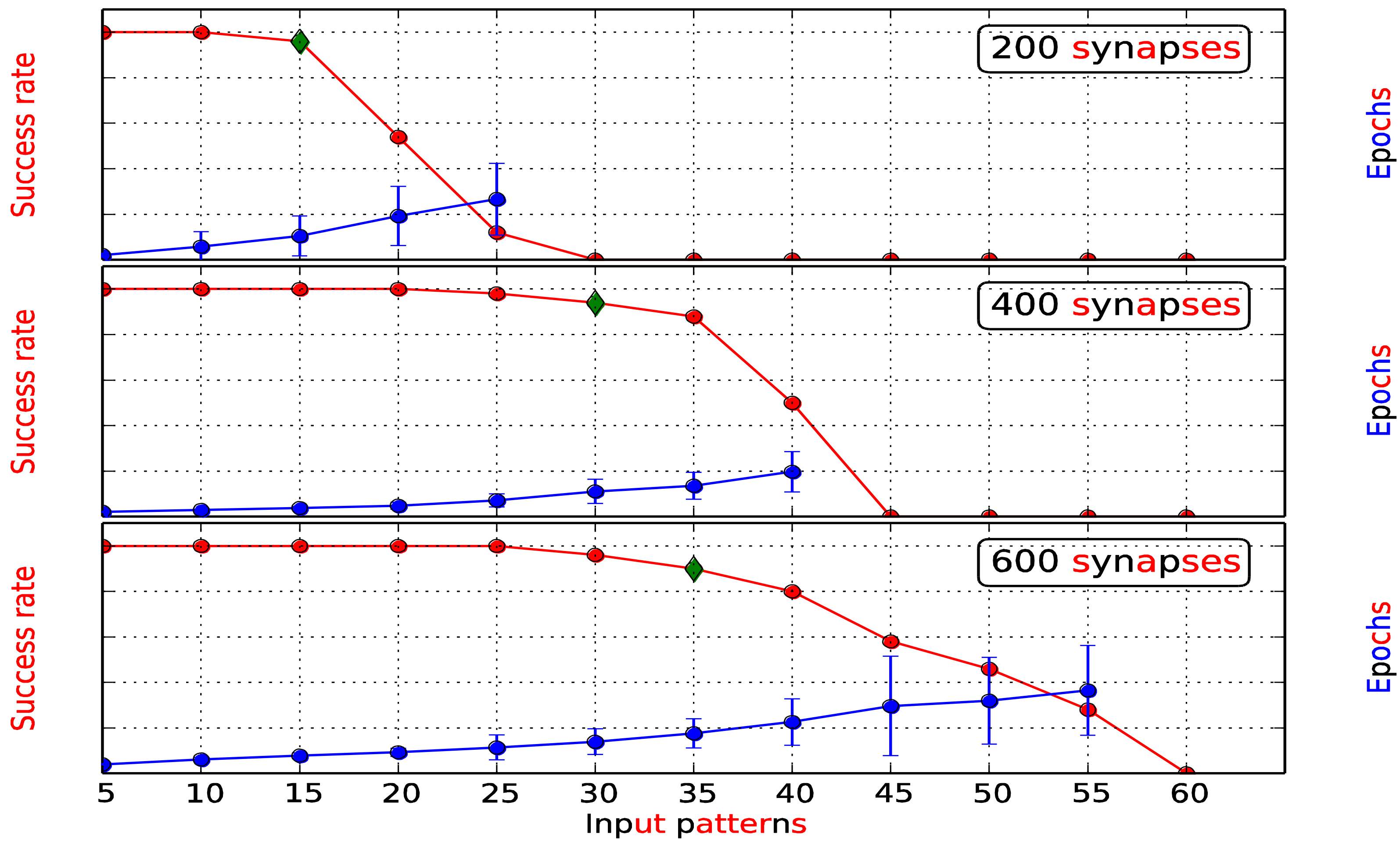


Illustration of the proposed training algorithm.

What is the memory capacity of a single SPAN neuron?



Part II: SNN systems. STDM.

5. SNN systems for pattern recognition, classification and regression

- Pattern recognition:
  - Time vs Rate coding of the outputs
- Classification:
  - Fixed structure
  - Evolving structure
  - One output neuron spikes (the first) vs ensemble of spiking neurons
  - Deep learning structure
- Regression
  - Additional output layer for the output values of each input pattern
  - wkNN output calculation
  - Rate-based coding of continuous values of a regression
- Early event prediction

Evolving SNN (eSNN) for classification and regression

- eSNN: Creating and merging neurons based on localised information (Kasabov, 2007; Wysoski, Benuskova and Kasabov, 2006-2009)
- 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) Calculate the similarity between weight vectors of newly created neuron and existing neurons: IF similarity > Threshold THEN Merge newly created neuron with the most similar neuron

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

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

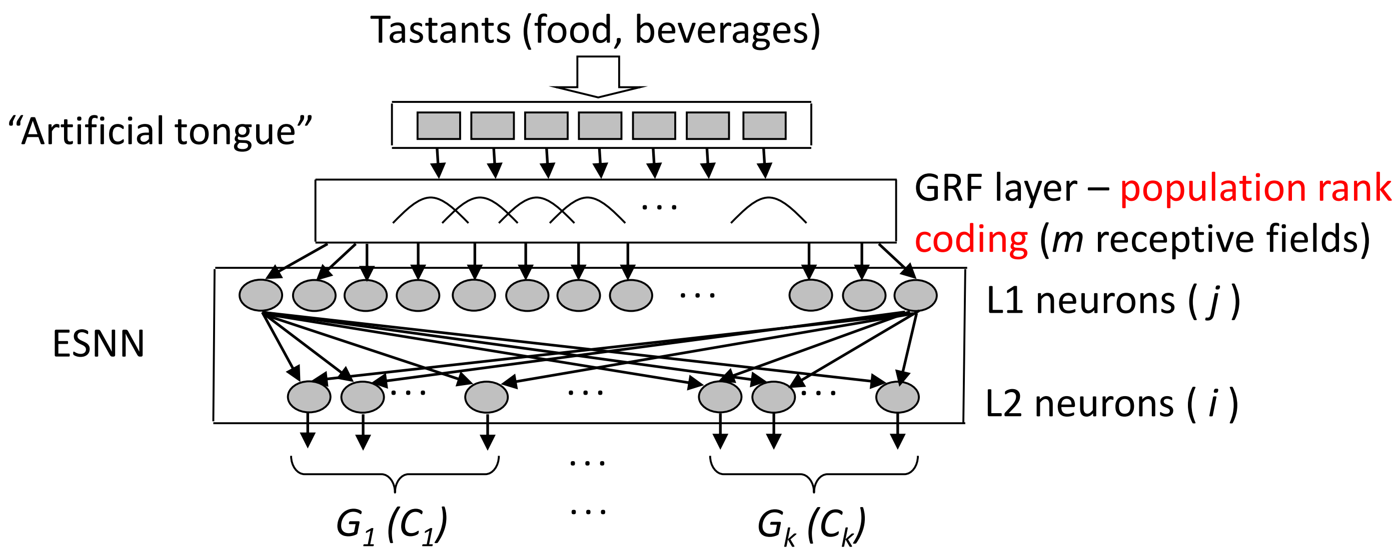
  d) Update the corresponding threshold ϑ:

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

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

Example: eSNN for taste recognition and classification

(S.Soltic, S.Wysoski and N.Kasabov, Evolving spiking neural networks for taste recognition, Proc.WCCI 2008, Hong Kong, IEEE Press)

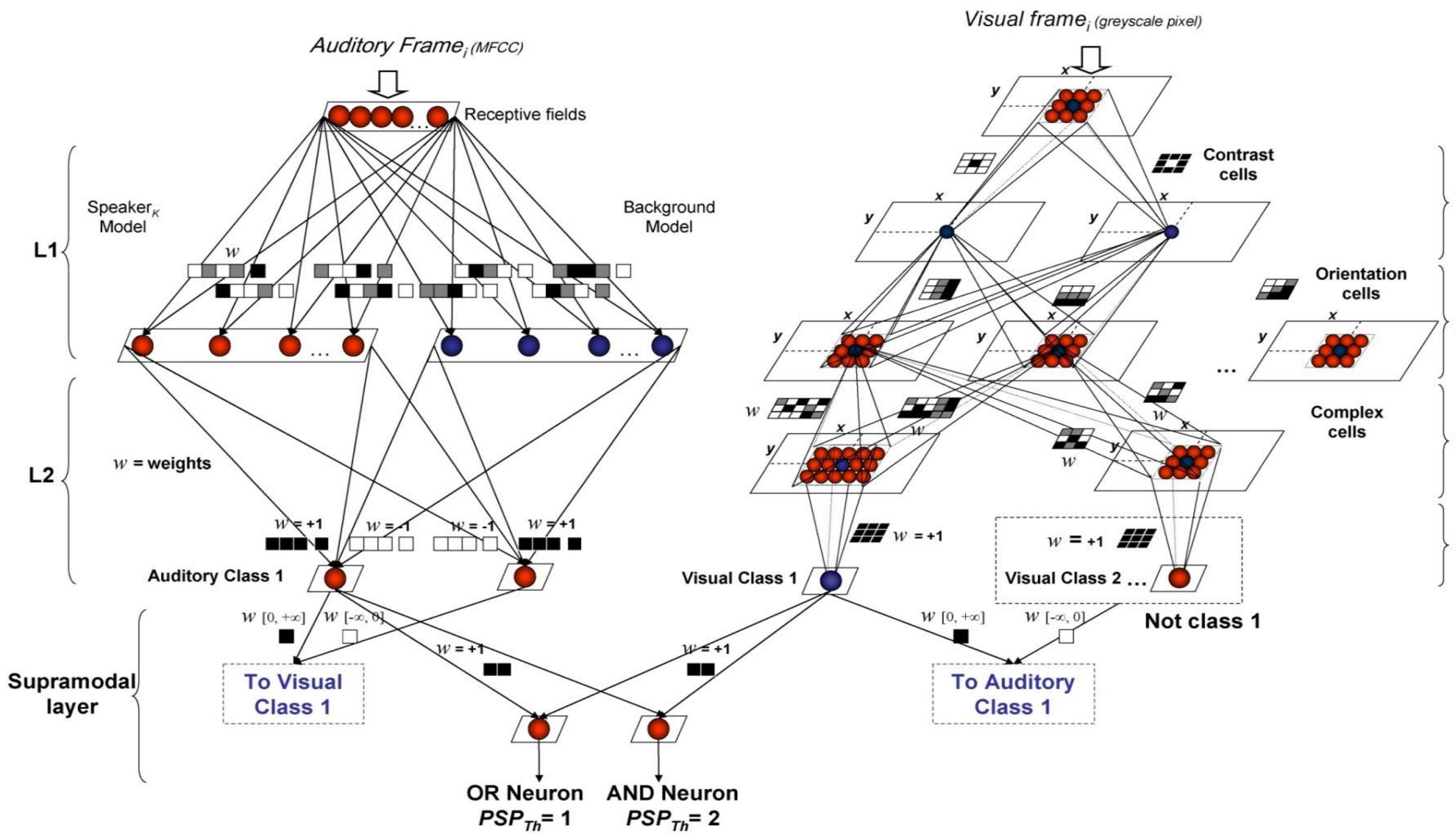


- The L2 layer evolves during the learning stage (S_Θ).
- Each class C_i is represented with an ensemble of L2 neurons
- Each ensemble (G_i) is trained to represent one class.
- The latency of L2 neurons' firing is decided by the order of incoming spikes.

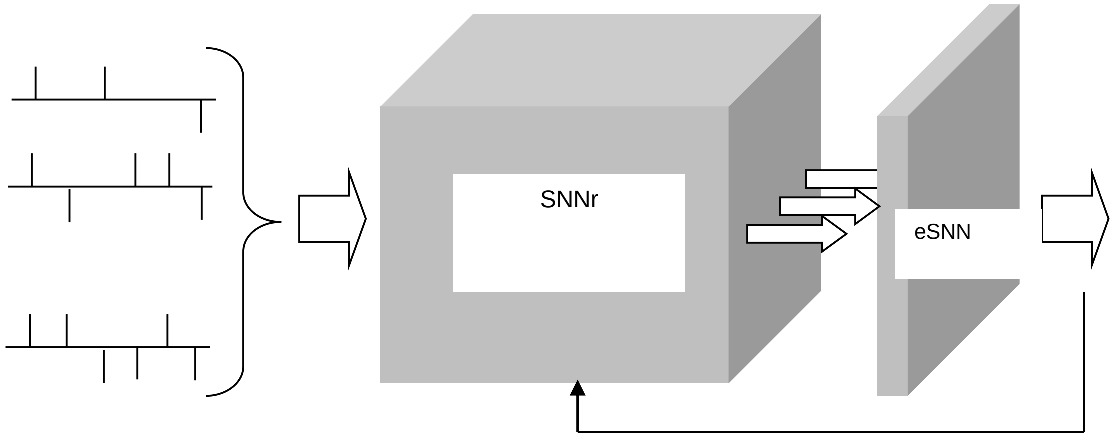
Deep SNN learning in eSNN for integrated audio-visual data classification

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).

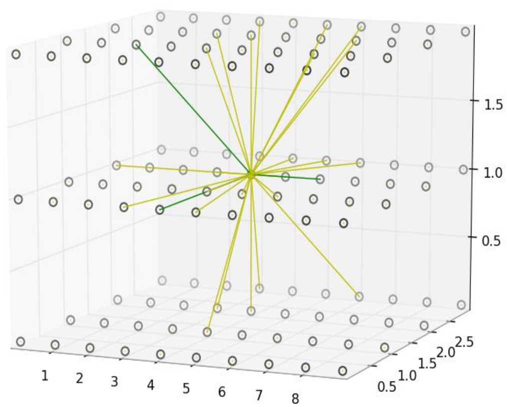


6. Neuromorphic spatio-temporal data machines. NeuCube



Architecture of the STDM:

- Temporal inputs (features) are converted into spike trains
- Inputs are mapped into a 3D SNN cube/reservoir (SNNc)
- Classifier (e.g. eSNN, SPAN, etc.) are connected to neurons from the SNNc
- SNNc recurrent connections, e.g. small world connections



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

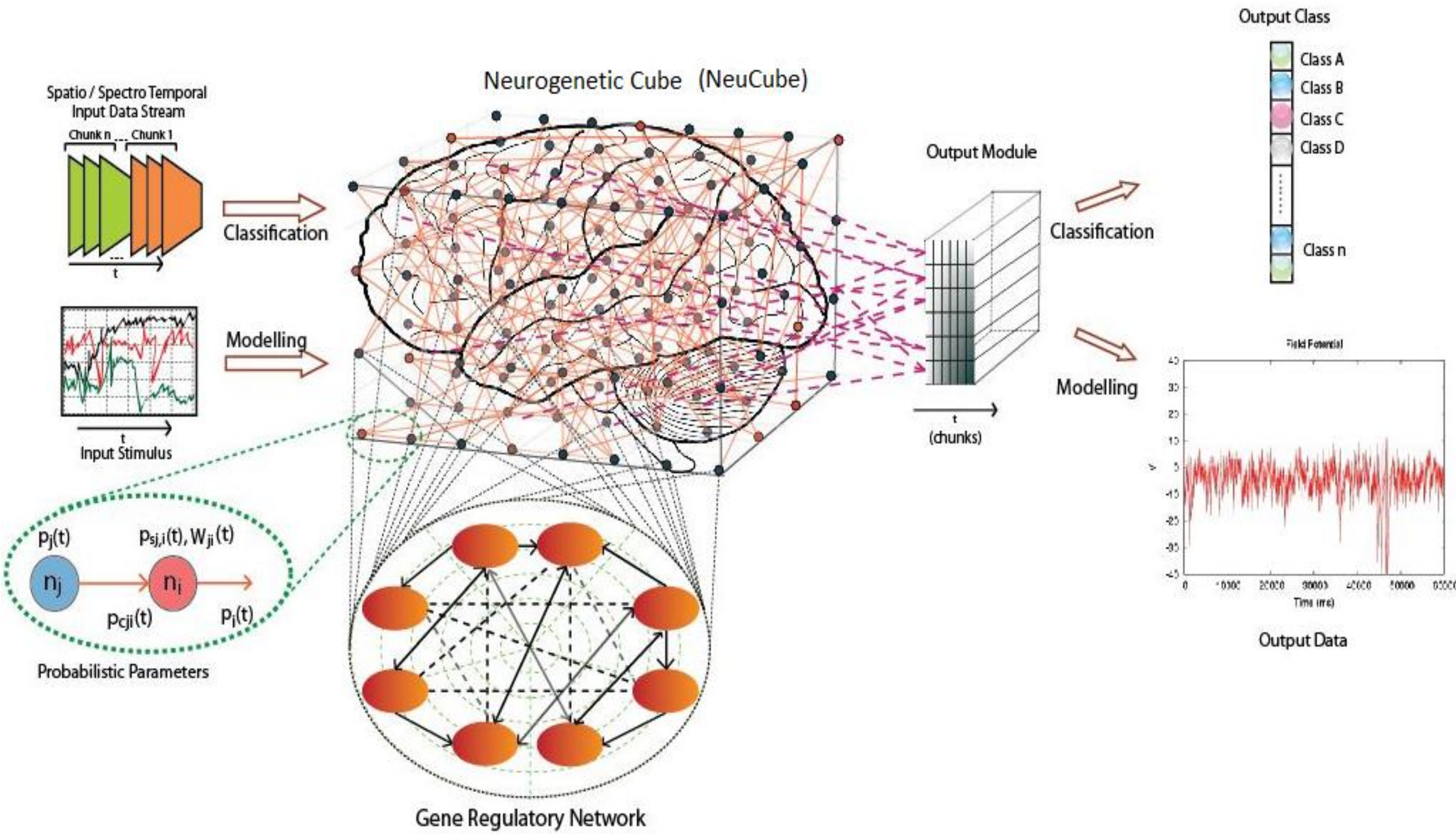
Learning:

- Unsupervised (e.g. STDP; spike time delay) in the SNNc;
- Supervised (the output classifier or regressor)

- Adaptive, deep learning of complex spatio-temporal patterns
- Fast , on-line operation

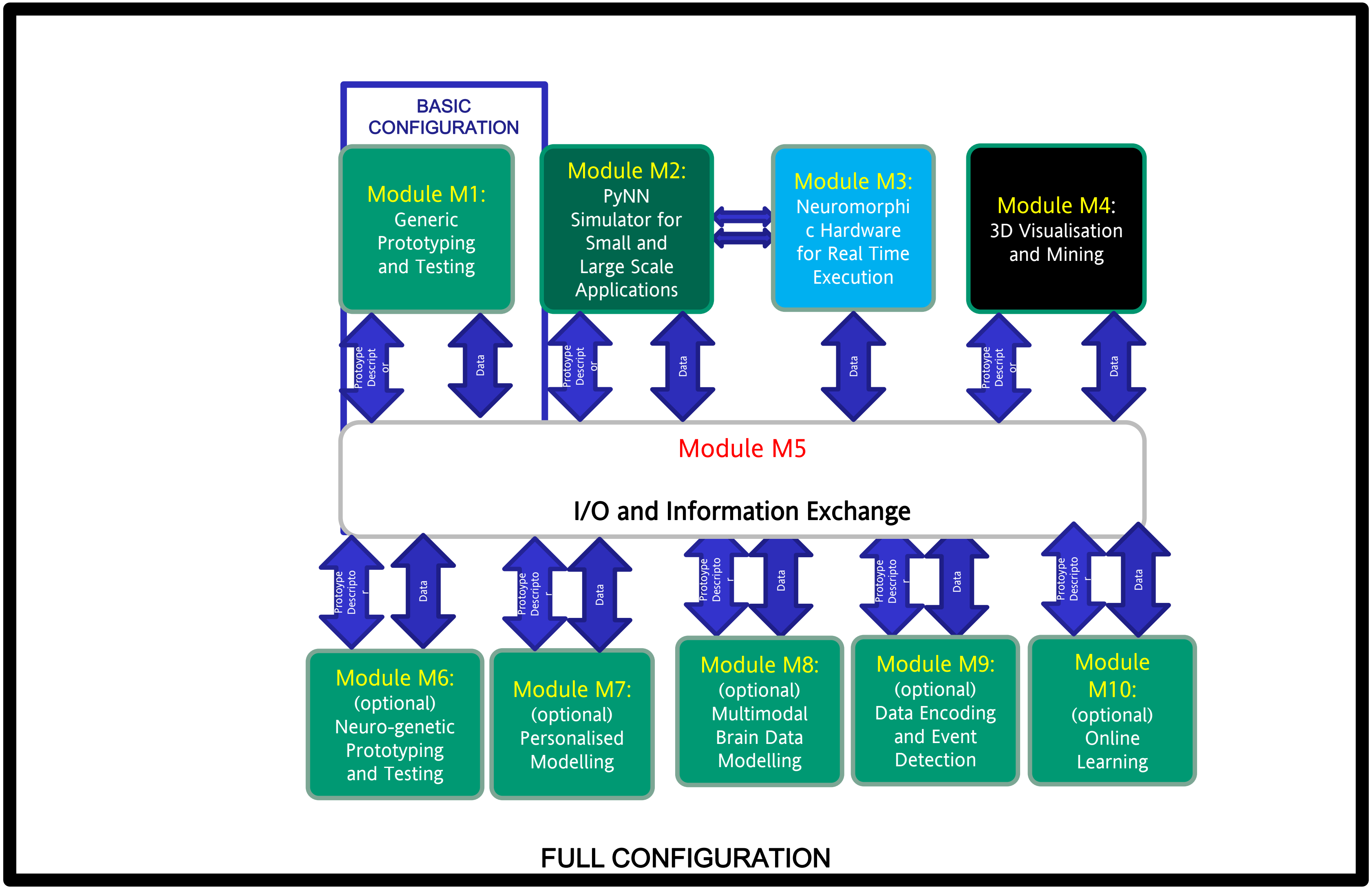
The NeuCube Architecture

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



NeuCube: A Neuromorphic Spatio-Temporal Data Machine and Development System

N.Kasabov, et al, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube neuromorphic framework, Neural Networks, The Big Data Special Issue, vo.78, 1-14, 2016.



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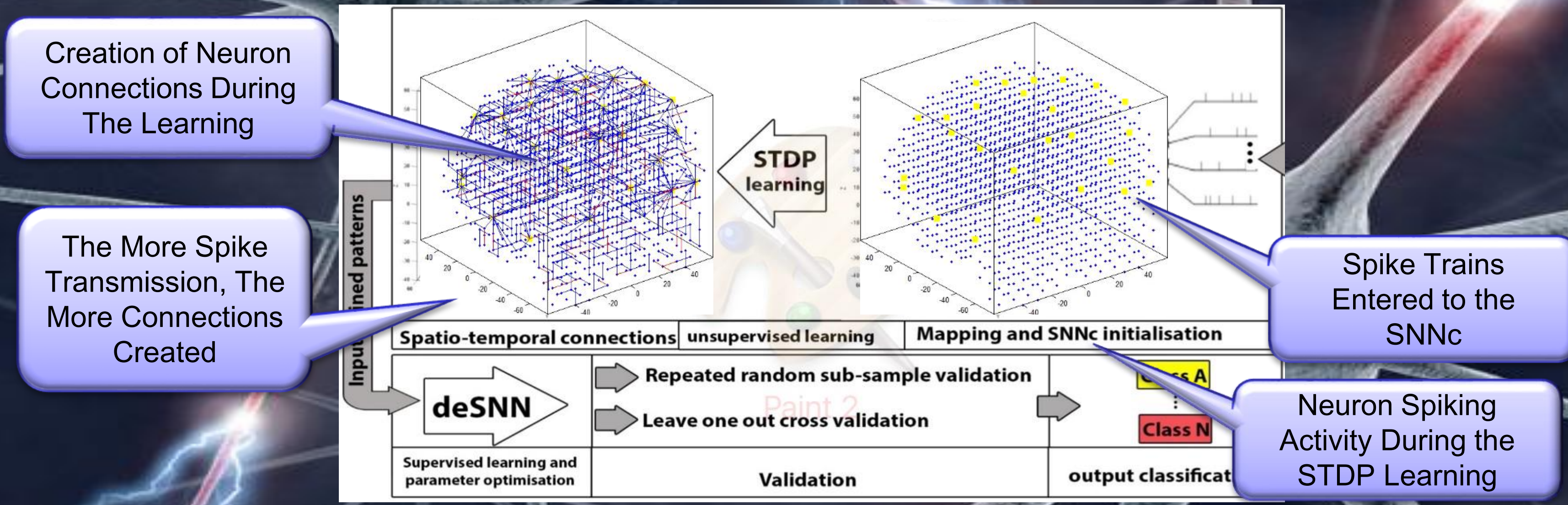
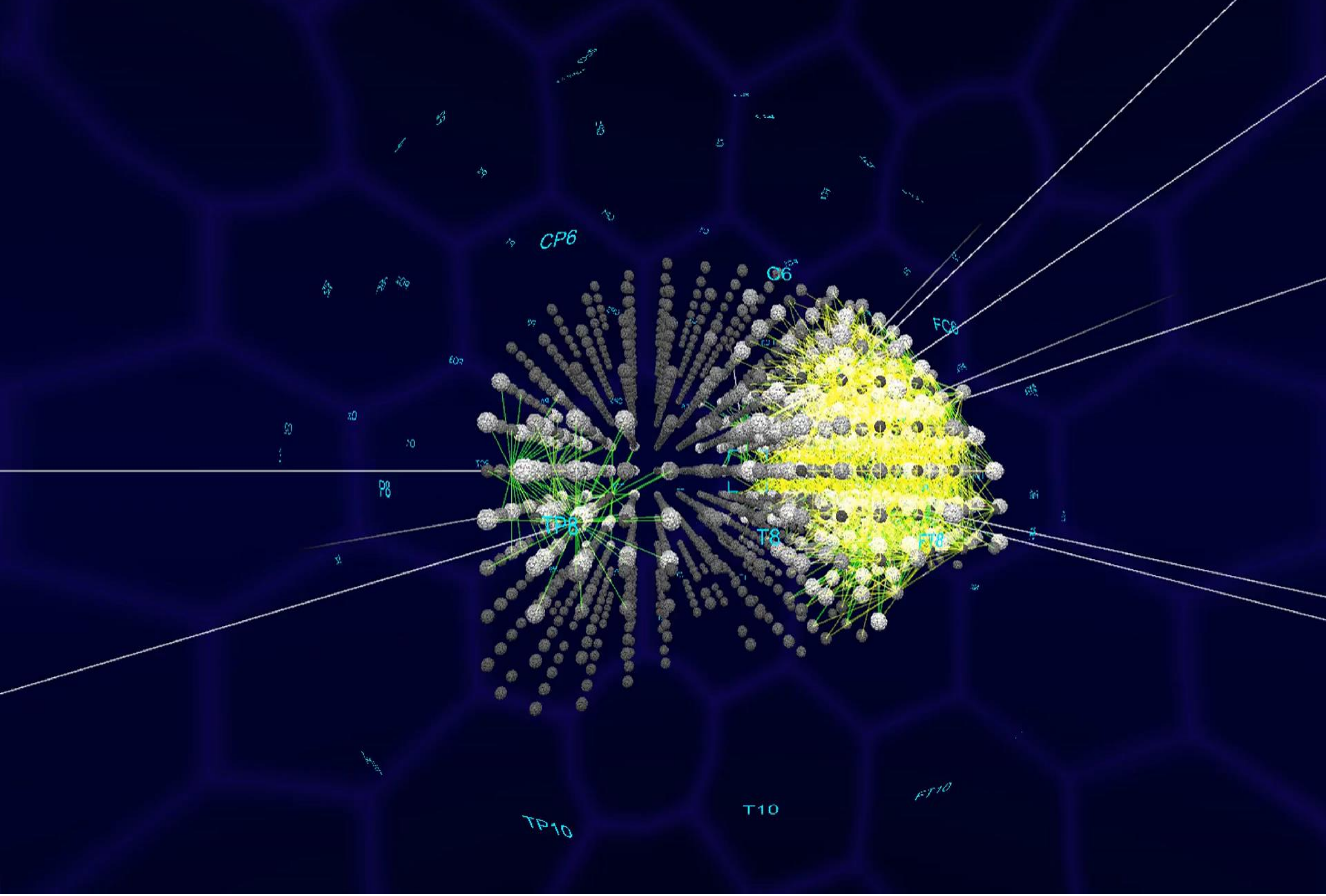
Deep learning of spatio-temporal patterns from streaming data

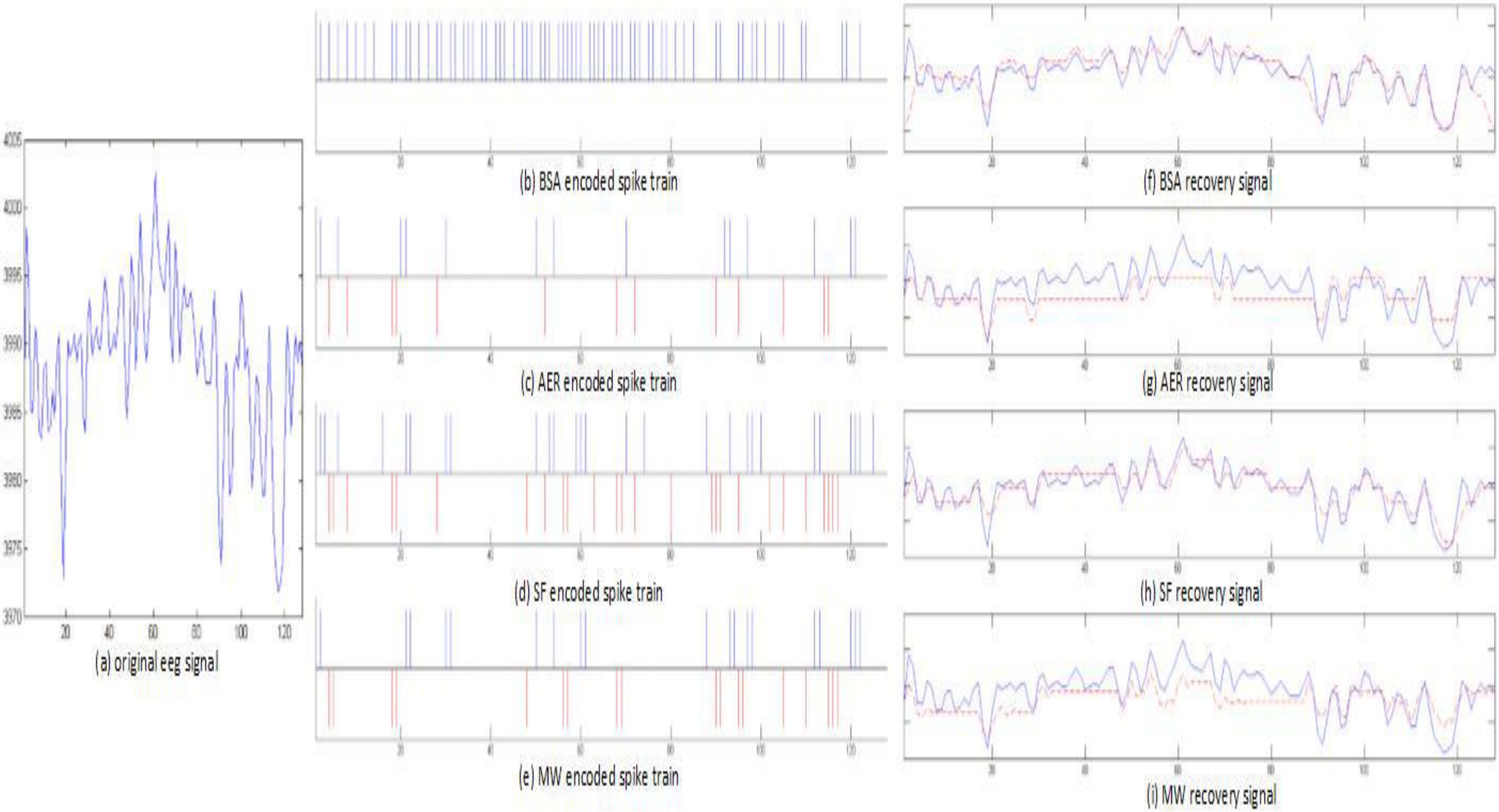



CP6
C6
FC6
P8
TP8
T8
FT8
TP10
T10
FT10

Steps in designing a SNN application system

a) Input data transformation into spike sequences;
(b) Mapping input variables into spiking neurons
(c) Unsupervised learning spatio-temporal spike sequences in a scalable 3D SNN reservoir;
(d) On-going learning and classification of data over time;
(d) Dynamic parameter optimisation;
(e) Evaluating the time for predictive modelling
(f) Adaptation on new data, possibly in an on-line/ real time mode;
(g) Model visualisation and interpretation for a better understanding of the data and the processes that generated it.
(h) Implementation of the SNN model as both software and a neuromorphic hardware system (if necessary)

a) Input data encoding:
What constitutes a good encoding?



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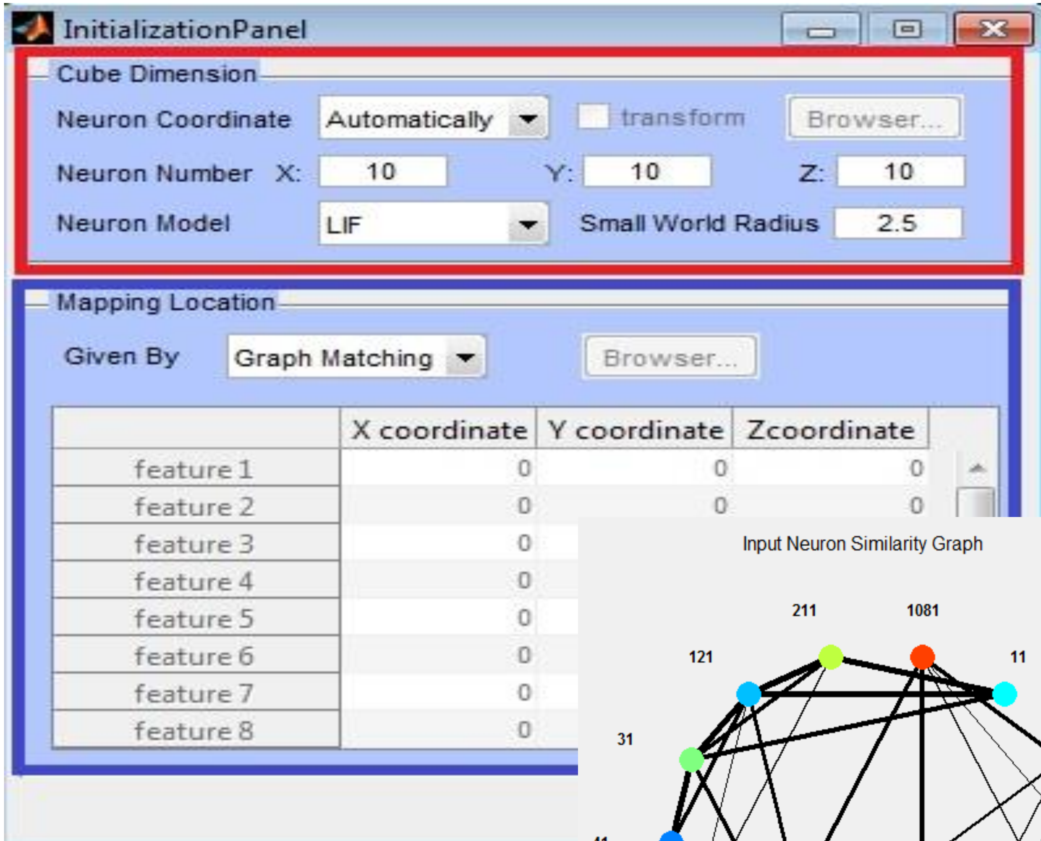
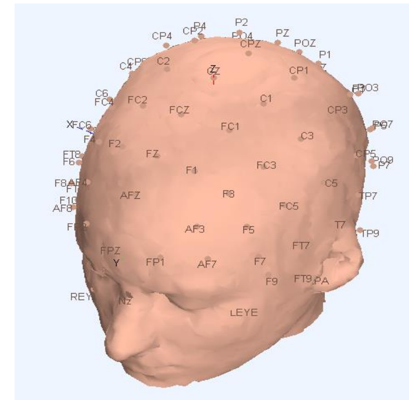
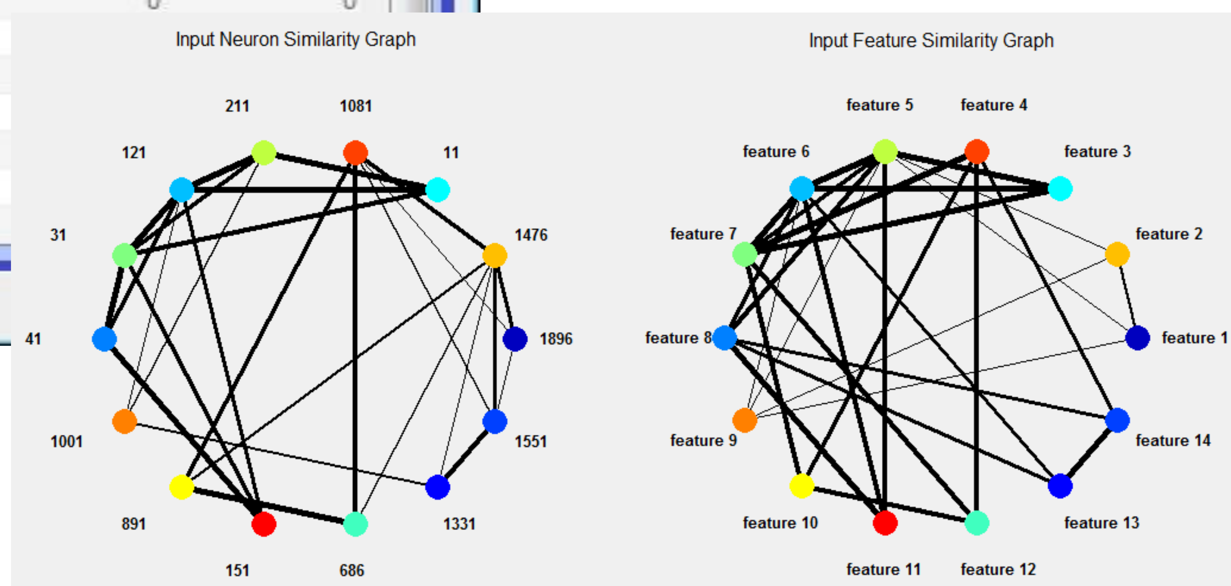
b) Spatial mapping of input variables into a SNN architecture

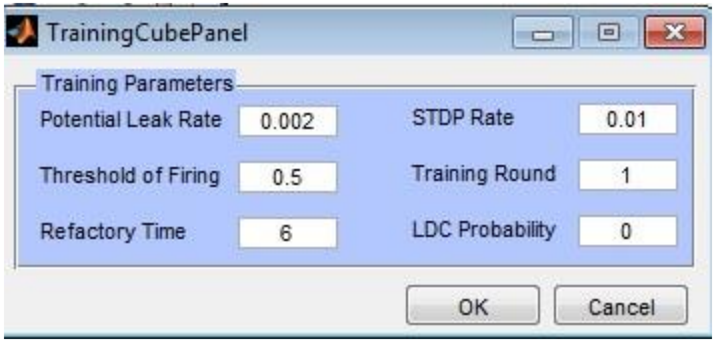
(Enmei Tu, Nikola Kasabov, and Jie Yang, Mapping Temporal Variables into the NeuCube Spiking Neural Network Architecture for Improved Pattern Recognition, Predictive Modelling and Understanding of Stream Data, IEEE Transactions of Neural Networks and Learning Systems, 2016)

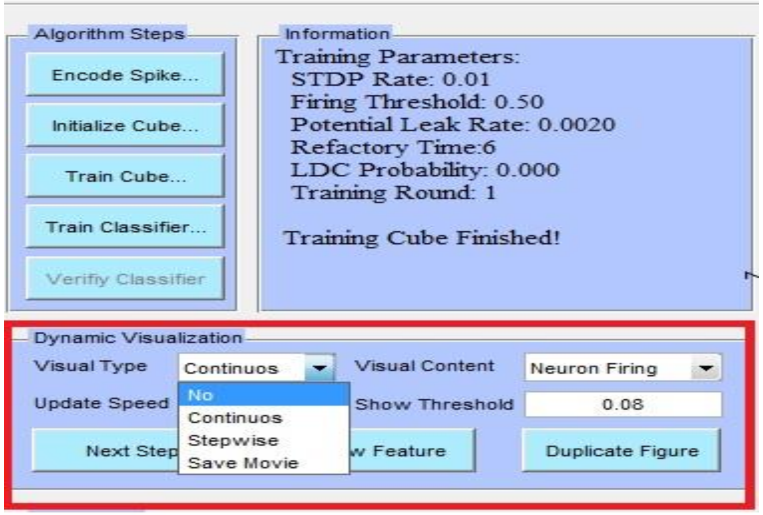


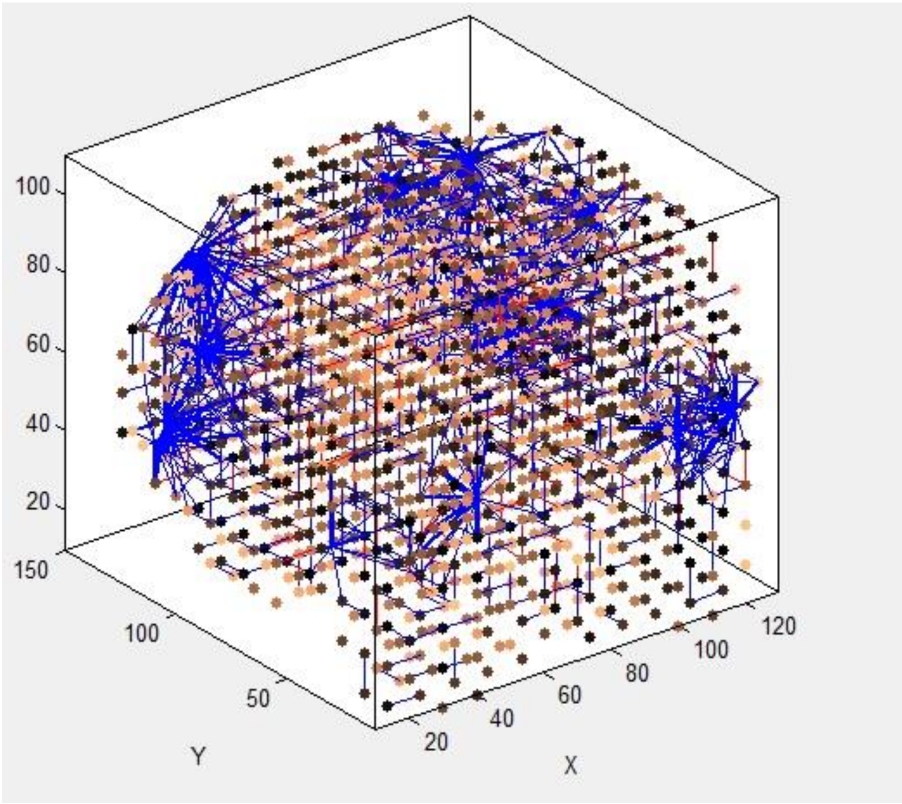




C) Deep unsupervised learning of spatio-temporal patterns in a SNNcube

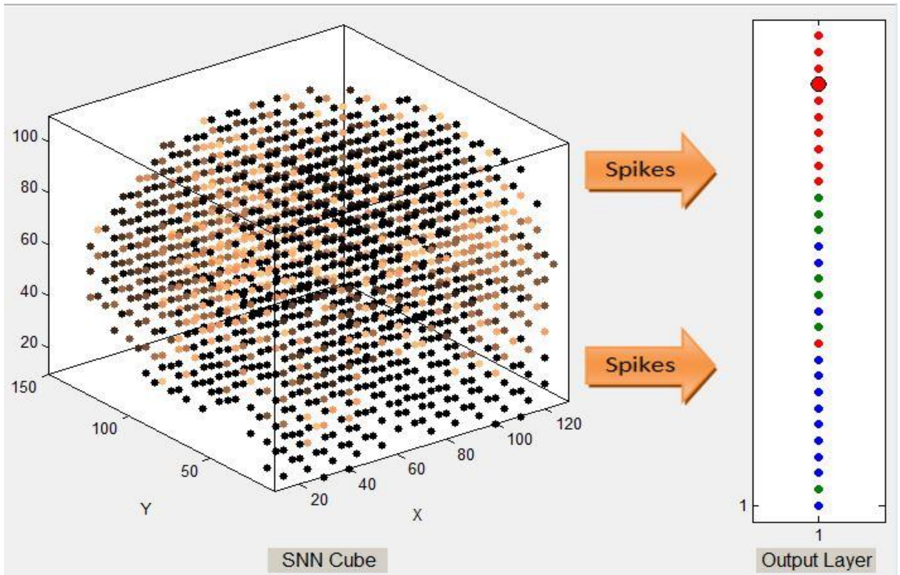


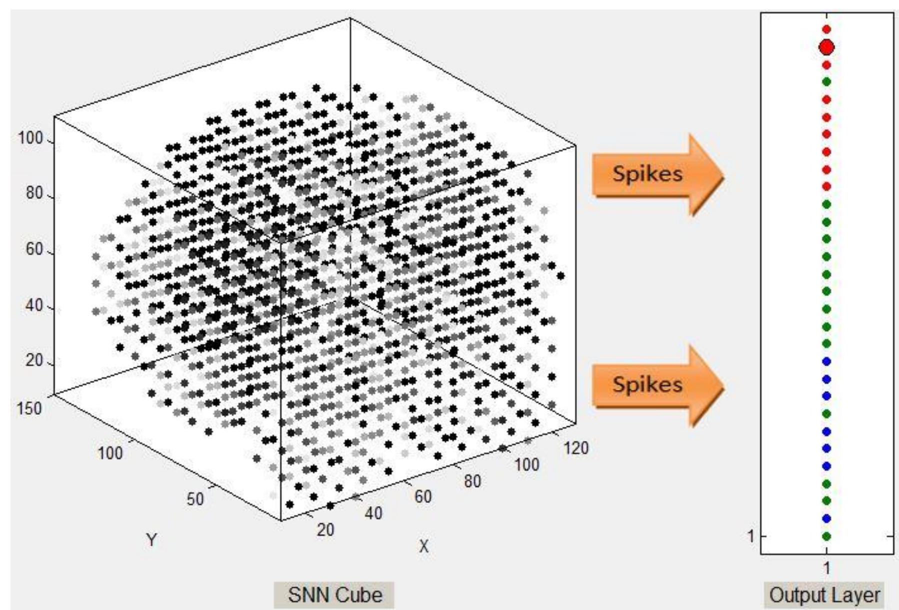




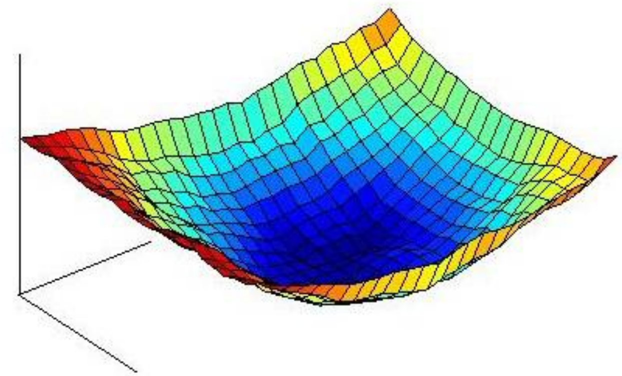
d) Classification/regression

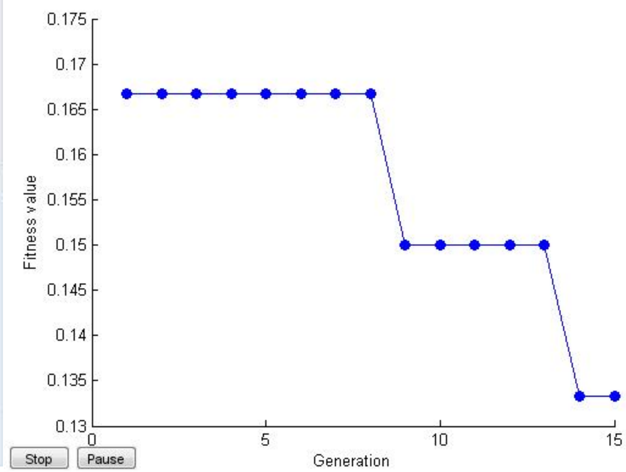
- Output classifiers, e.g. deSNN
- Visualisation of connection strengths – impact;
- Visualization of firing order – timing.





e) Parameter optimisation





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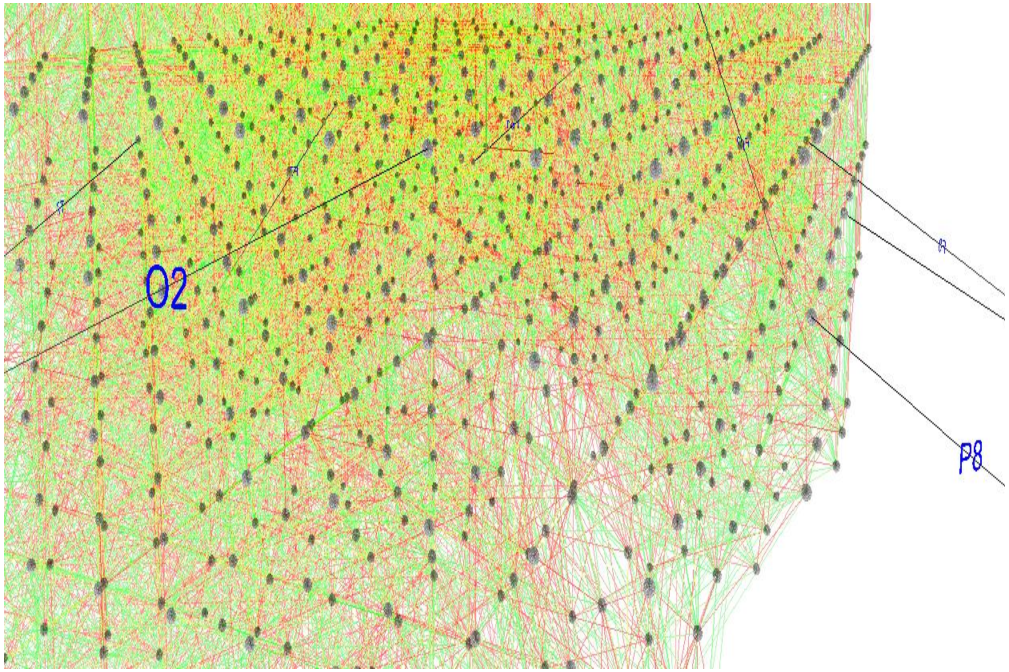
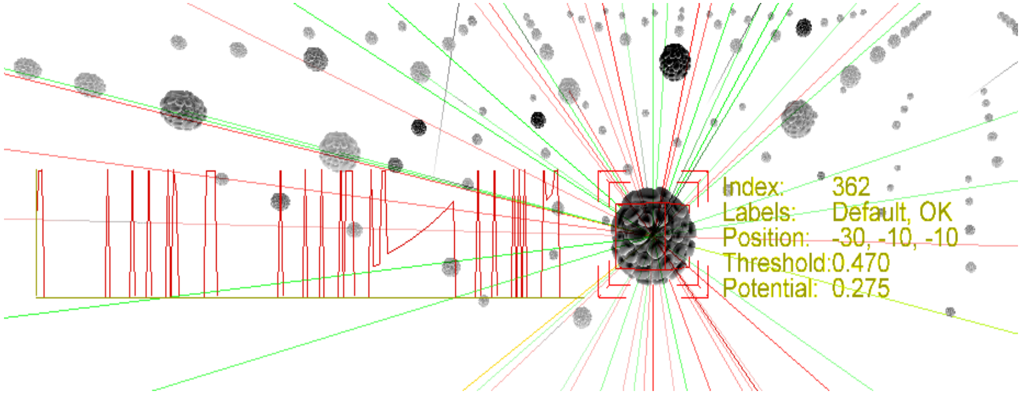
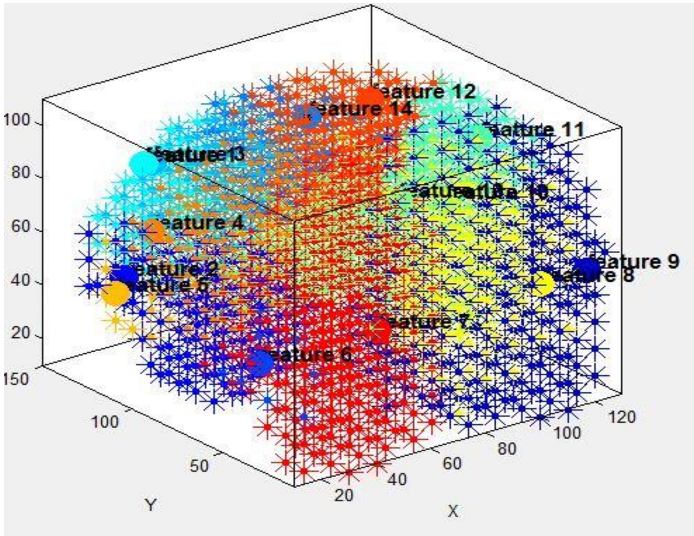
f) 3D Visualisation of SNN models

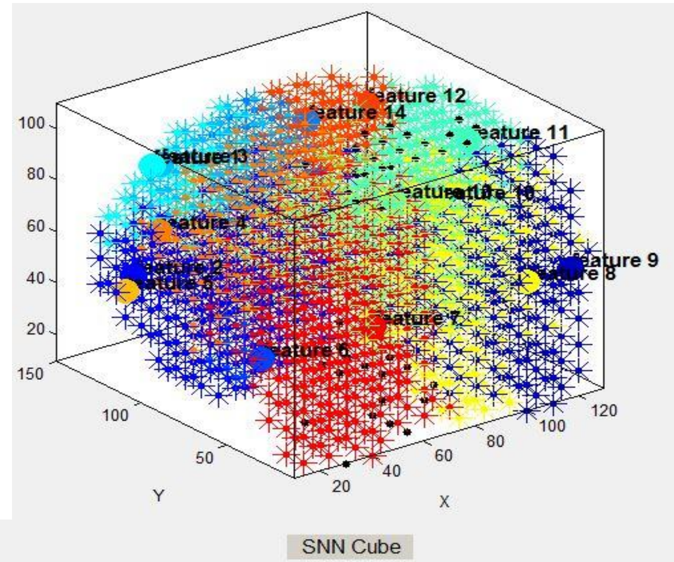


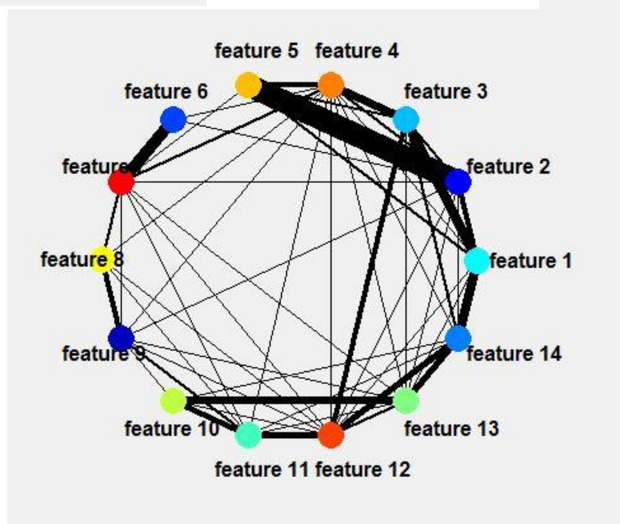


g) Clustering of neurons in a SNNcube and feature selection

- according to connection weights;
- according spiking activity;
- inter-variable cluster interaction







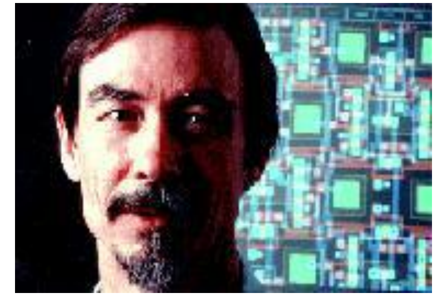
h) Predictive modelling with SNN vs traditional ML techniques

- Whole input spatio-temporal patterns can be learned
- Different temporal length of samples for training and recall is possible
- Chain-fire after deep learning in the SNNcube, so that if only part of new input information is entered the learned pattern in the SNNcube can be triggered leading to accurate prediction
- Setting an early spike threshold in the classifier/regressor using the rank-order learning
- The system is responsive to changes in the input data through spike encoding
- The system is adaptable on new data

7. Neuromorphic hardware systems

Hodgin- Huxley model (1952)

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

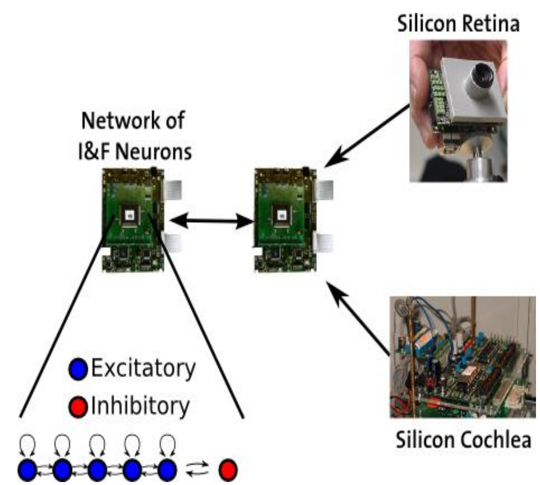


INI Zurich SNN chips (Giacomo Indivery, 2008 and 2012)

FPGA SNN realisations (McGinnity, Ulster, 2010);

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

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



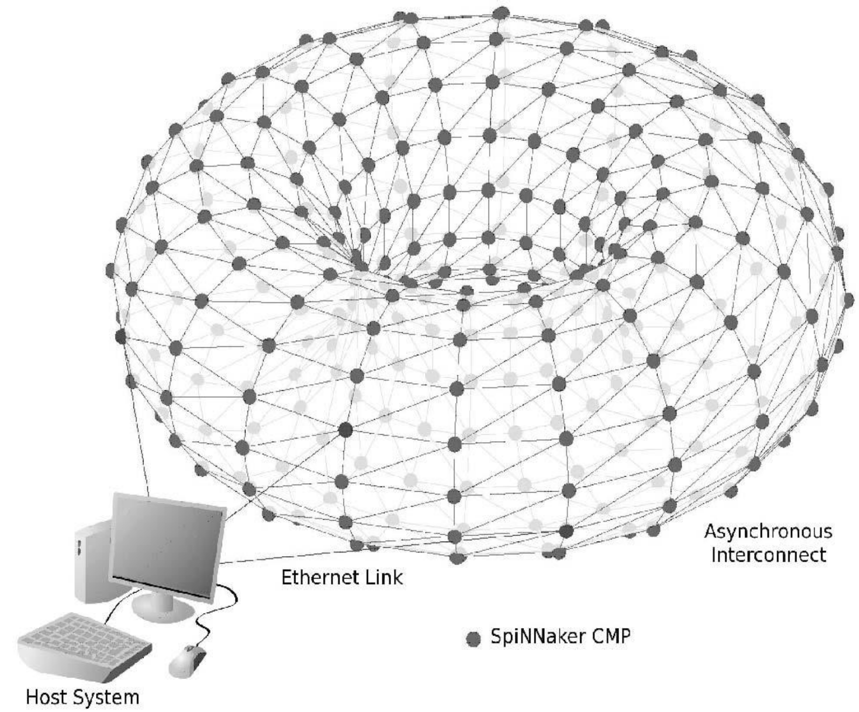
The Stanford U. NeuroGrid (Kwabena Boahen et al), 1mln neurons on a board, 63 bln connections ; hybrid - analogue /digital)

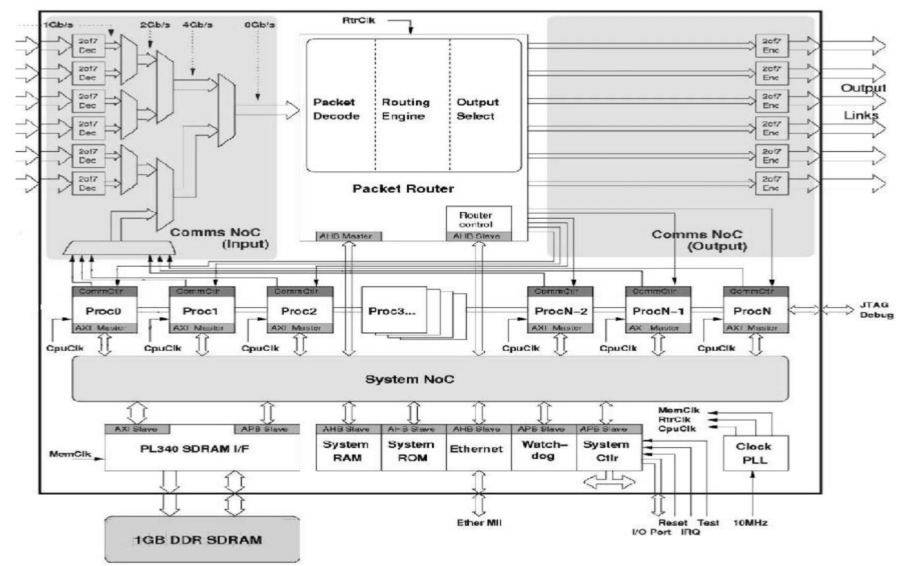
High speed and low power consumption.

SpiNNaker

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

- U. Manchester, Prof. Steve Furber;
- General-purpose, scalable, multichip multicore platform for the real-time massively parallel simulation of large scale SNN;
- 18 ARM968 subsystems responsible for modelling up to one thousand neurons per core;
- Spikes are propagated using a multicast routing scheme through packet-switched links;
- Modular system – boards can be added or removed based on desired system size;
- 1 mln neurons – 2014;
- 100mln neurons - 2018





Part III. SNN Applications for SSTD

Different types of SSTD:

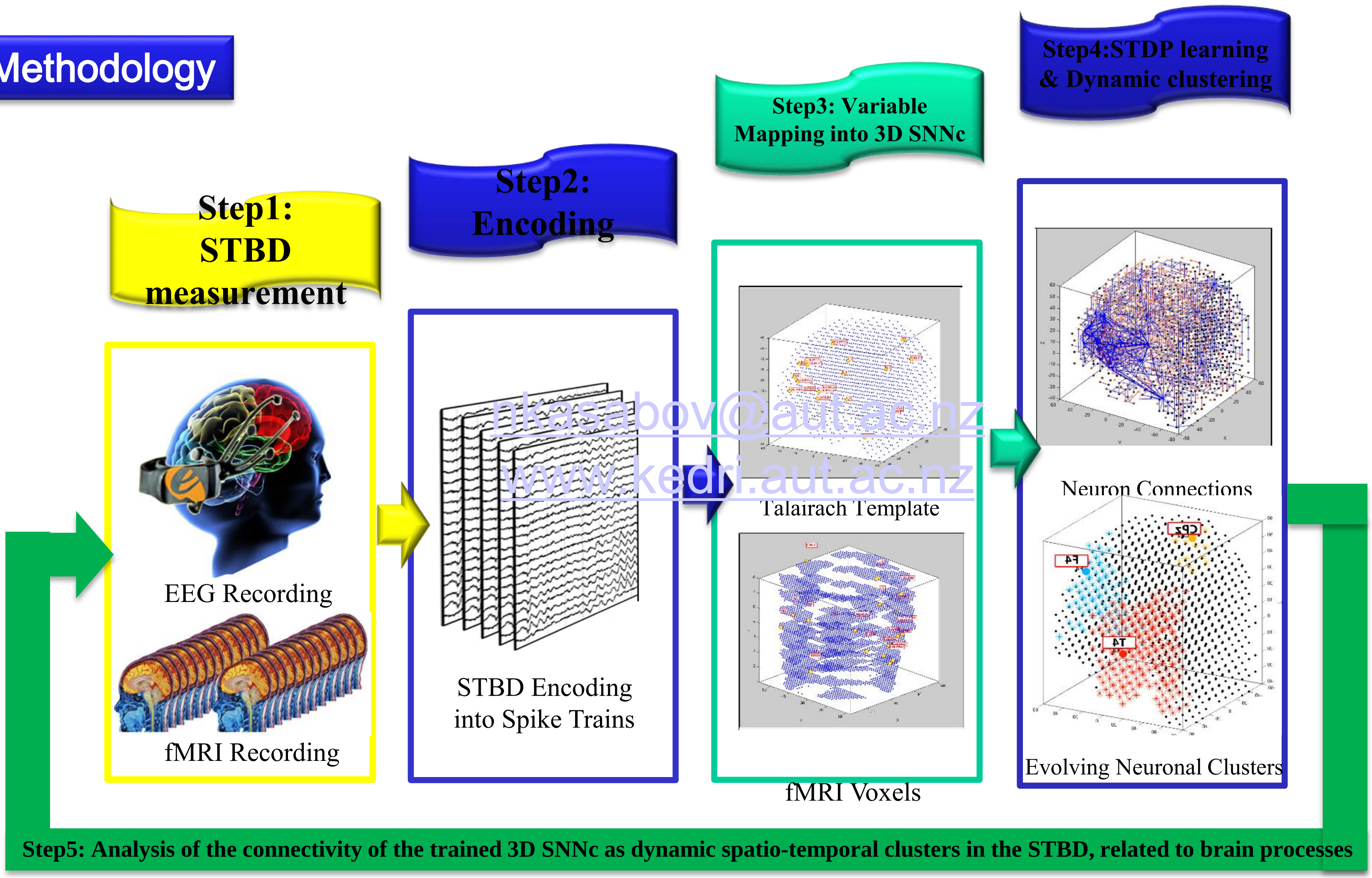
- Temporal (e.g. climate data)
- Spatio-temporal with fixed spatial location of variables (e.g. brain data)
- Spatio-temporal with changing locations of the spatial variables (e.g. moving objects)
- Spectro-temporal data (e.g. radio-astronomy; audio)

Different spatio-temporal characteristics:

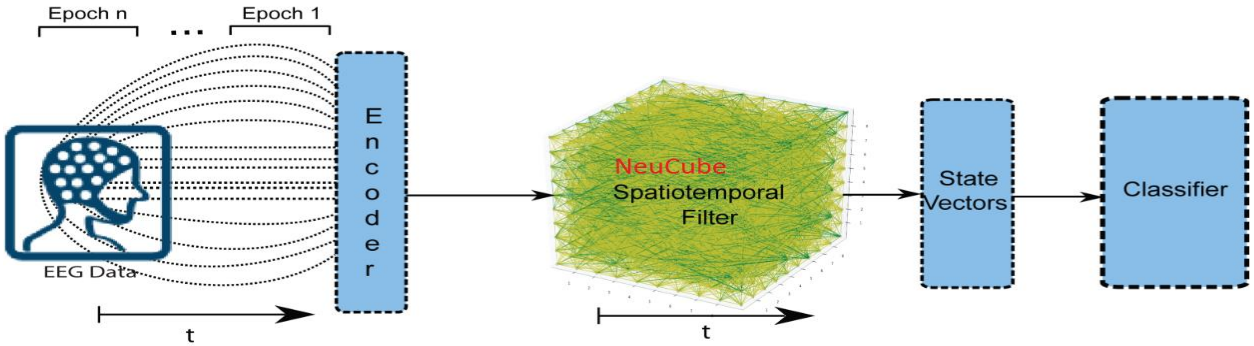
- Sparse features/low frequency (e.g. climate data; ecological data; multisensory data);
- Sparse features/high frequency (e.g. EEG brain signals; seismic data related to earthquakes);
- Dense features/low frequency (e.g. fMRI data);
- Dense features/high frequency (e.g. radio-astronomy data).

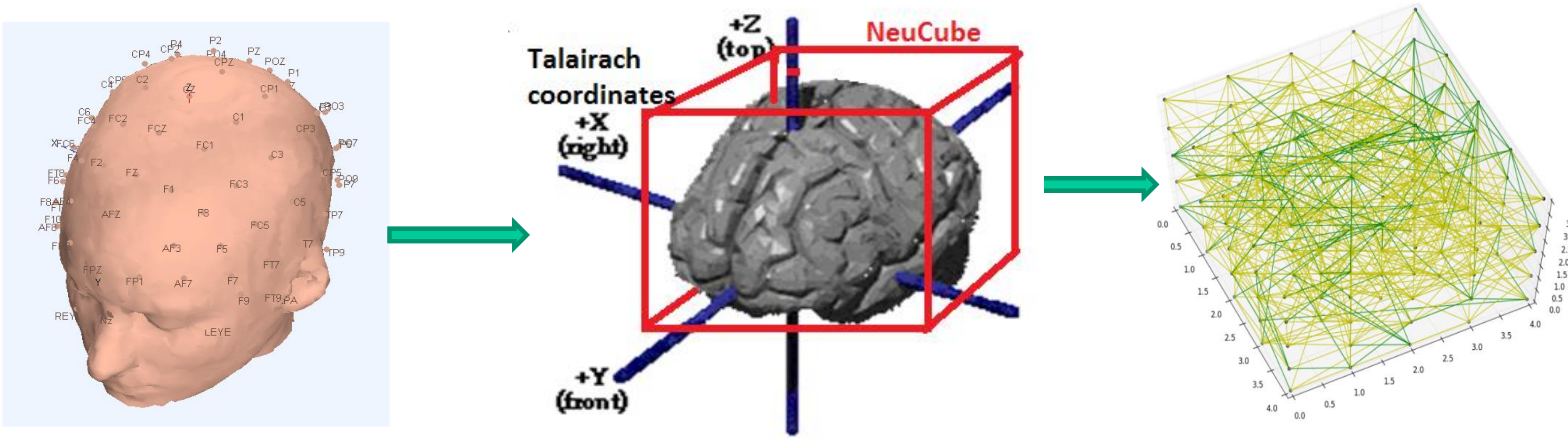
8. Spatio-temporal brain data (EEG, fMRI, integrated)

Methodology



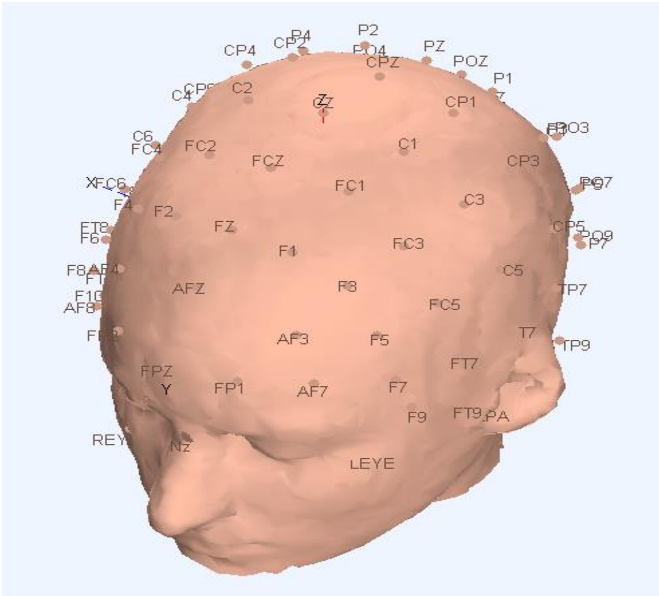
Mapping, learning and mining EEG data in NeuCube

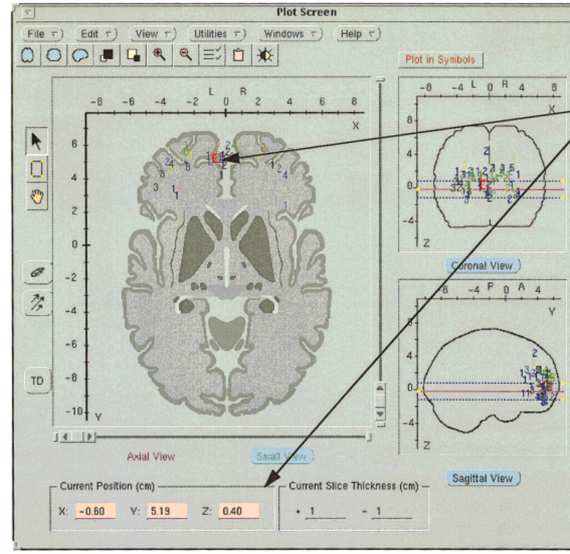




Same brain 3D coordinates (e.g. Talairach, MNI) are used for the allocated spiking neurons in the SNNc where the input data is mapped and the SNNc is analysed after training with the EEG data

Mapping EEG data into NeuCube





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**

Table 1

Anatomical locations of international 10–10 cortical projections

Labels	Talairach coordinates			Gyri		BA
	x avg (mm)	y avg (mm)	z avg (mm)			
FP1	−21.2 ± 4.7	66.9 ± 3.8	12.1 ± 6.6	L FL	Superior frontal G	10
FPz	1.4 ± 2.9	65.1 ± 5.6	11.3 ± 6.8	M FL	Bilat. medial	10
FP2	24.3 ± 3.2	66.3 ± 3.5	12.5 ± 6.1	R FL	Superior frontal G	10
AF7	−41.7 ± 4.5	52.8 ± 5.4	11.3 ± 6.8	L FL	Middle frontal G	10
AF3	−32.7 ± 4.9	48.4 ± 6.7	32.8 ± 6.4	L FL	Superior frontal G	9
AFz	1.8 ± 3.8	54.8 ± 7.3	37.9 ± 8.6	M FL	Bilat. medial	9
AF4	35.1 ± 3.9	50.1 ± 5.3	31.1 ± 7.5	L FL	Superior frontal G	9
AF8	43.9 ± 3.3	52.7 ± 5.0	9.3 ± 6.5	R FL	Middle frontal G	10

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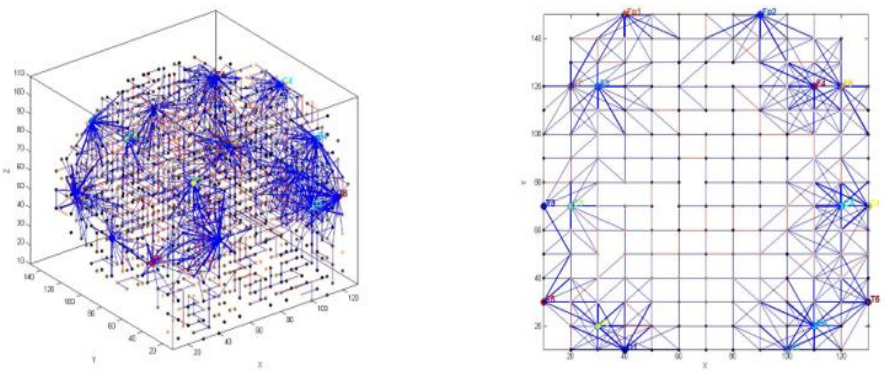
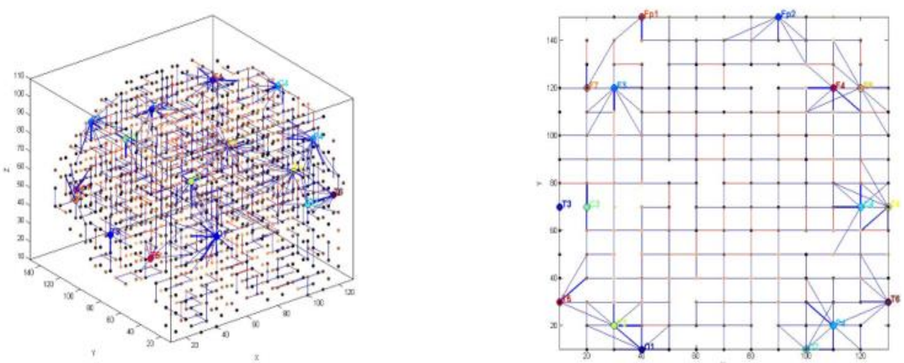
Can NeuCube predict brain states, in seconds? …in days? …. in years?

Predicting microsleep (in seconds)

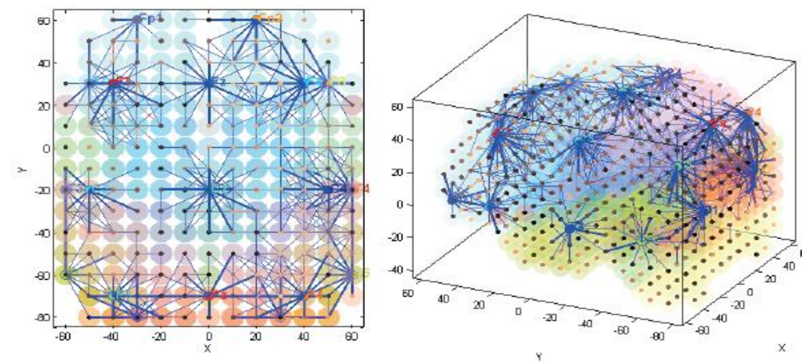


a)SNNcube connectivity based on pre-responsive event

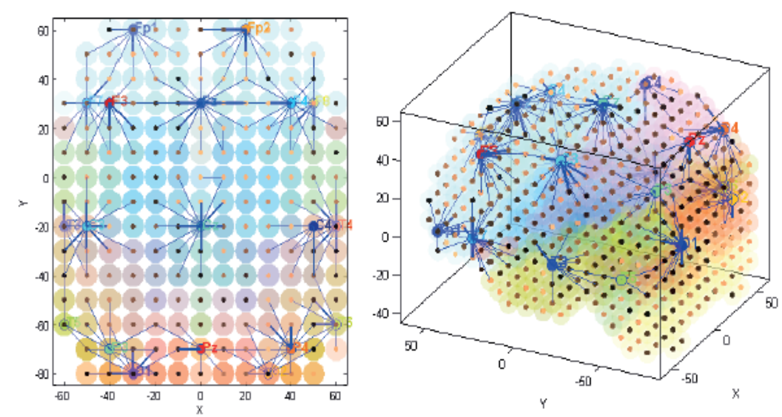


b)SNNcube connectivity based on pre-micro sleep event

Predicting progression of MCI to AD (months)



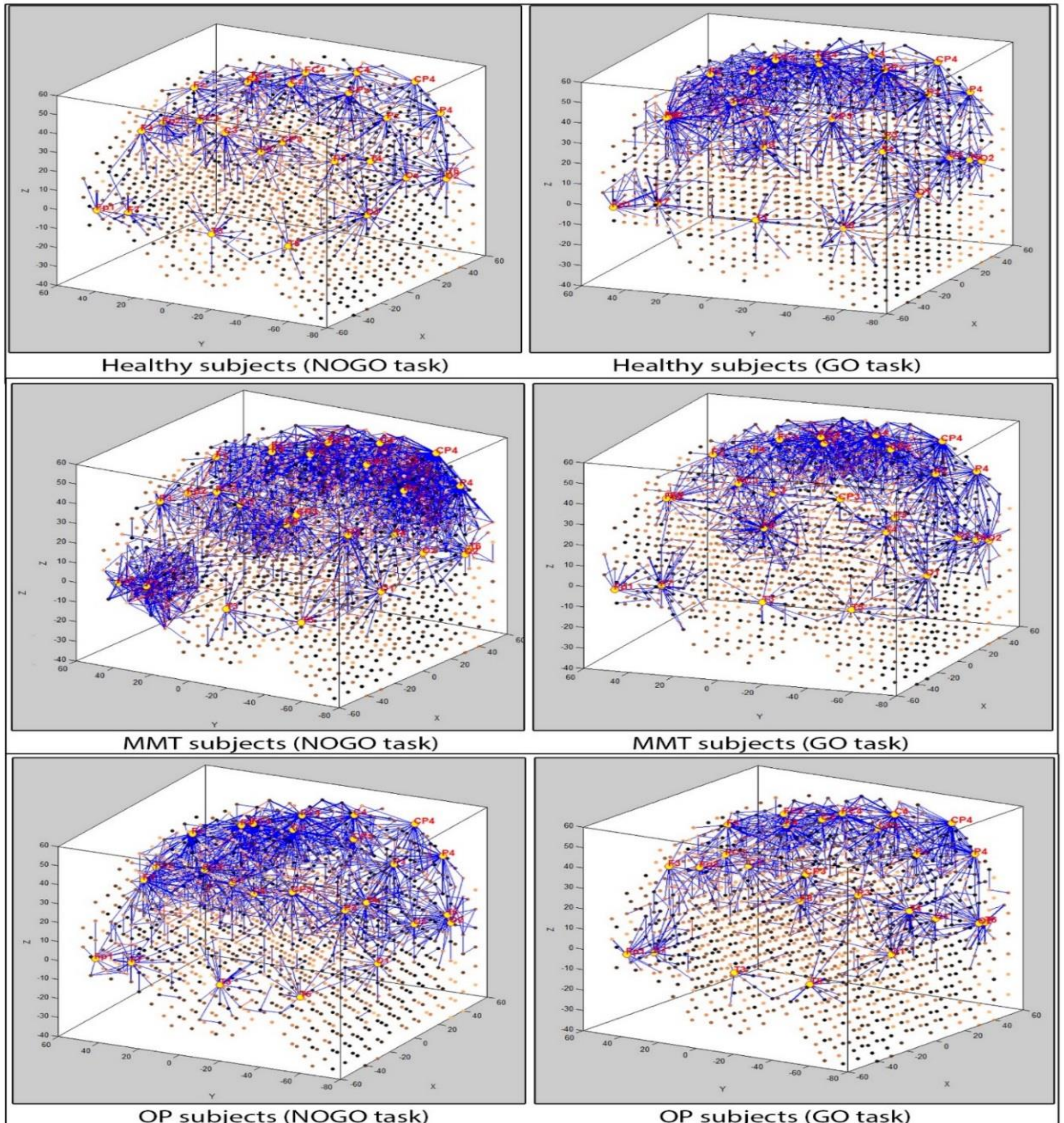
(a) EEG signal collected at t_0.



(b) EEG signal collected at t_1.

Understanding and predicting addicts' response to treatment

E. Capecci, N. Kasabov, G.Wang, R.Kydd, B.Russel Analysis of connectivity in a NeuCube spiking neural network trained on EEG data for the understanding and prediction of functional changes in the brain: A case study on opiate dependence treatment, Neural Networks, (2015), http://dx.doi.org/10.1016/j.neunet.2015.03.009; also IEEE Tr BME 2016.



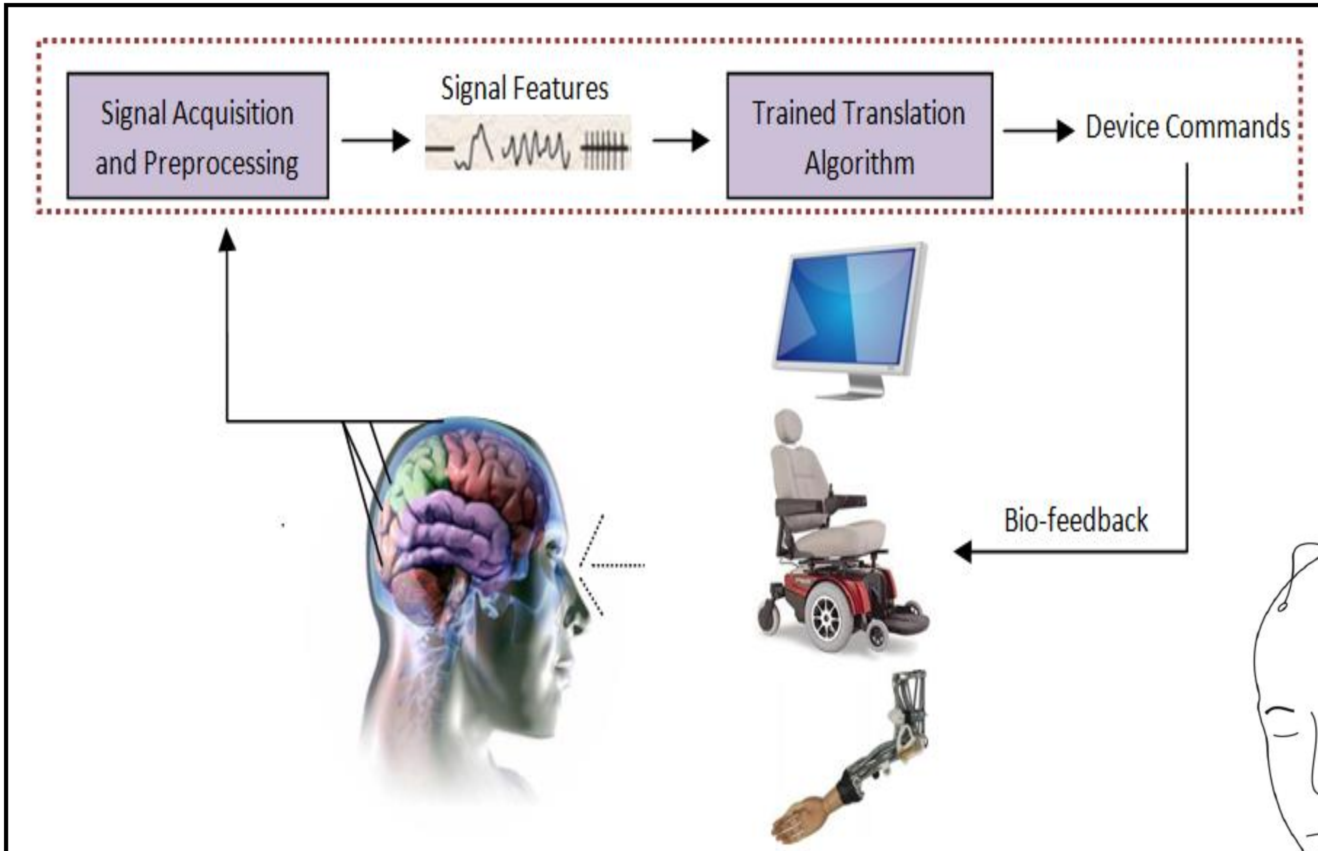
Tracing and interpreting dynamic brain activities in the GO/NOGO task performed by three subject groups:

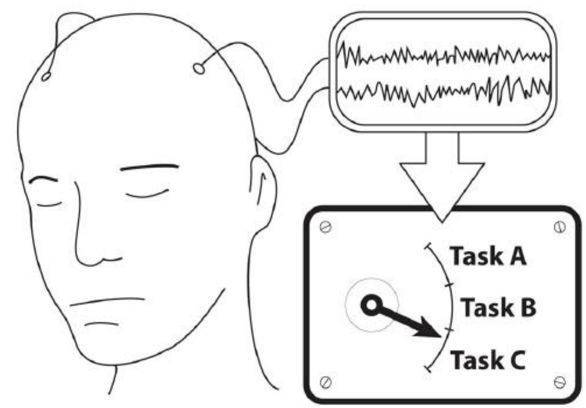
- healthy subjects CO);

- addicts on Methadone treatment (MMT);

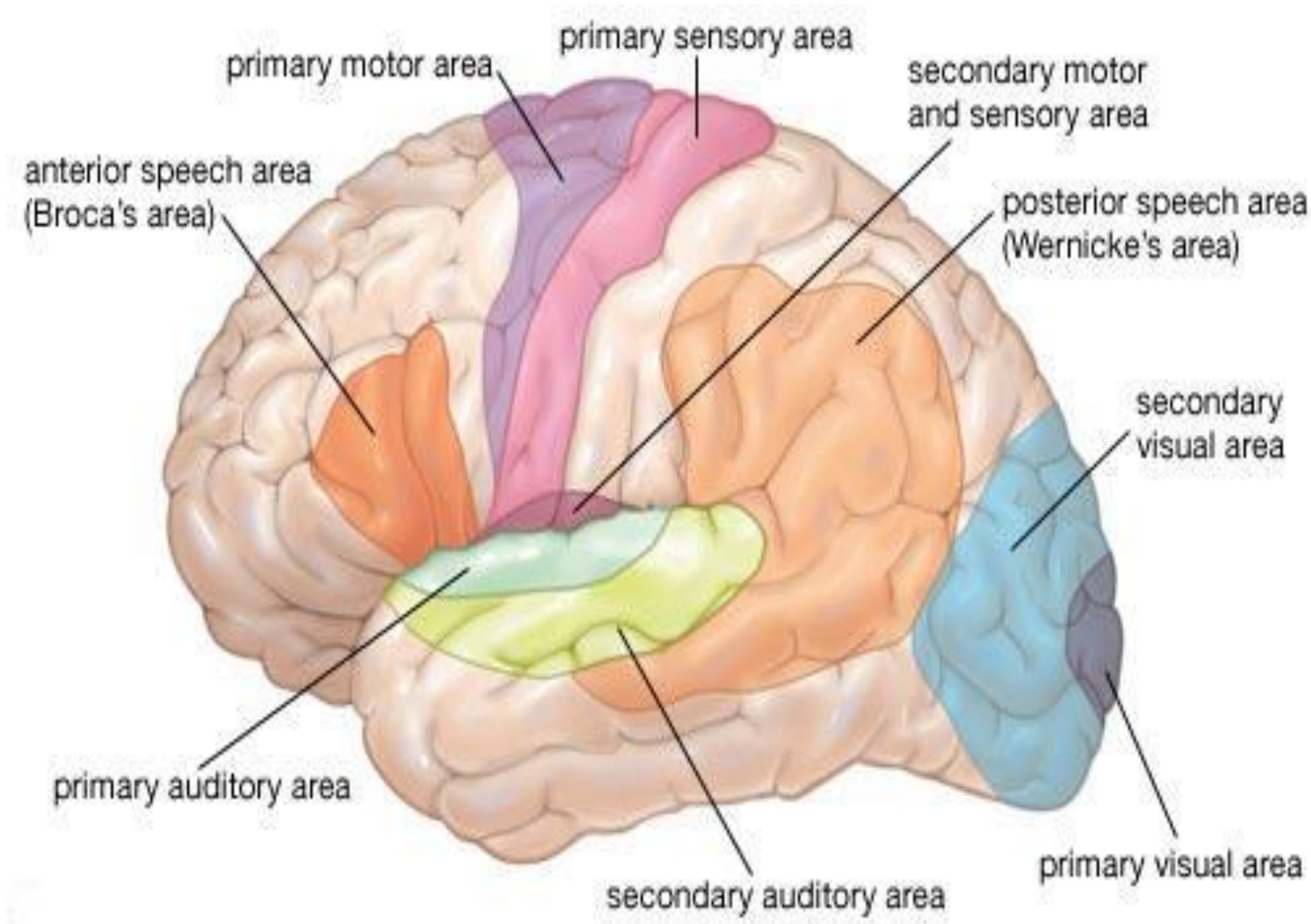
- addicts on opiates (OP), i.e. no treatment

Brain Computer Interfaces (BCI)



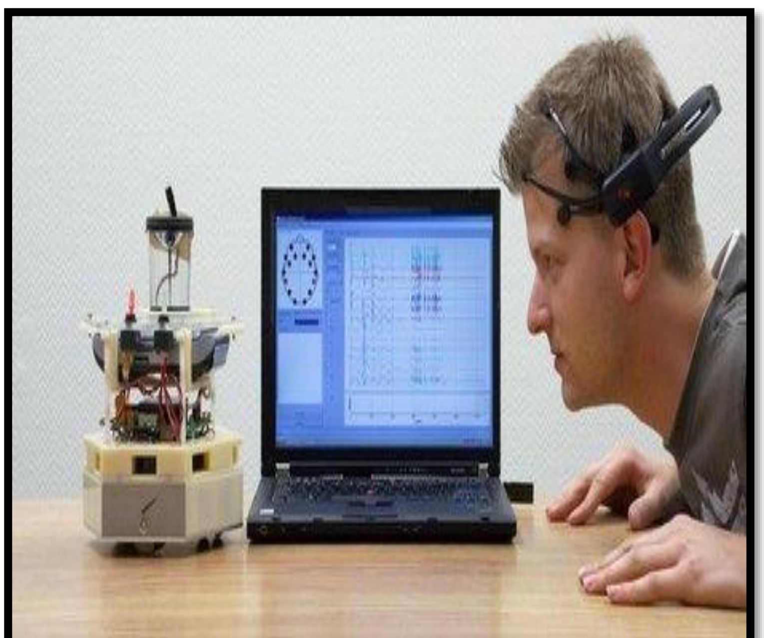


Different parts of the brain control different functions



NeuCube for BCI

- Brain-Computer Interfaces (BCIs) are interfaces that allow humans to communicate directly with computers or external devices through their brains (e.g. EEG signals)
- Experiments with the WITH robot from KIT Japan.
- Neuro-rehabiltation and neuro-prosthetics (with CASIA Prof. Hou)

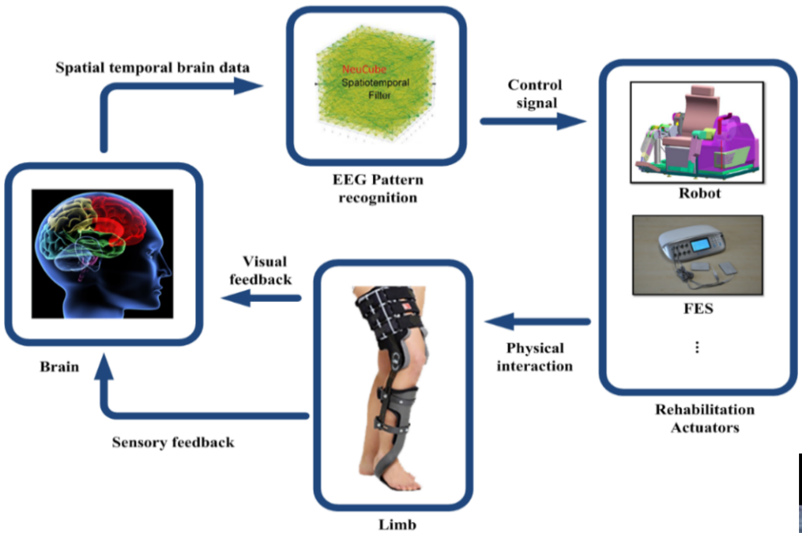


http://www.nzherald.co.nz

nkasabov@aut.ac.nz www.kedri.info

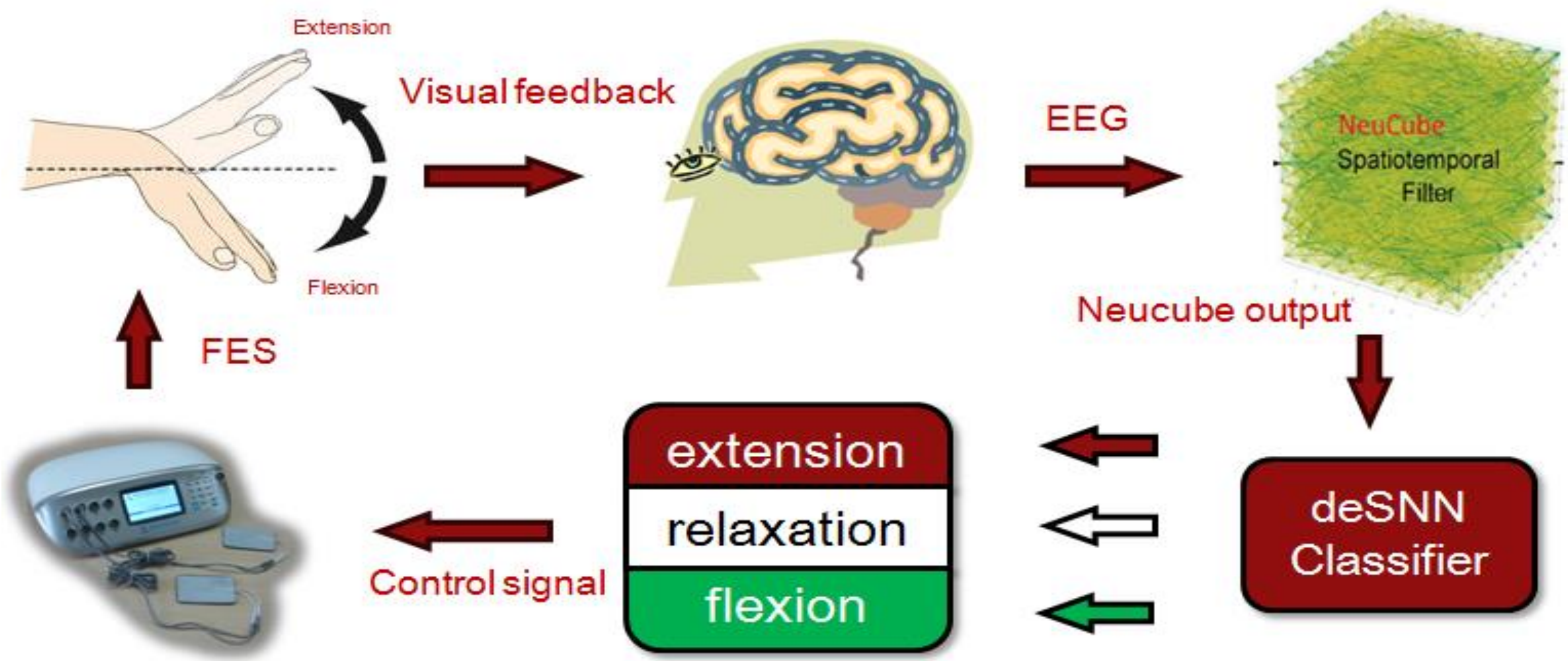
Personalised BCI and neurorehabilitation robotics

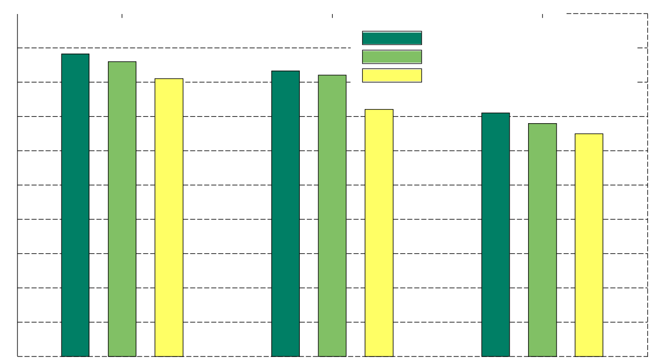
(with CASIA China)



Classification of EEG data for Neurorehabilitation

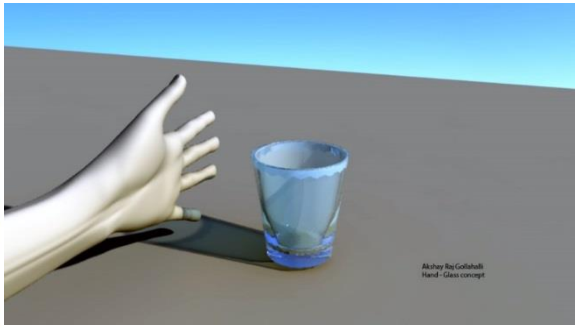
(with CASIA: Prof.Hou, Dr Chen and Dr. Hu)



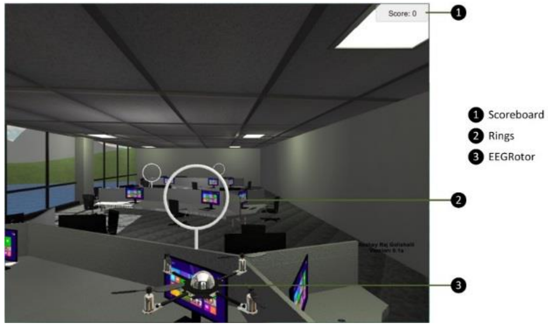


Assistive devices and cognitive games

Proof of concept for external device control in neurorehabilitation.



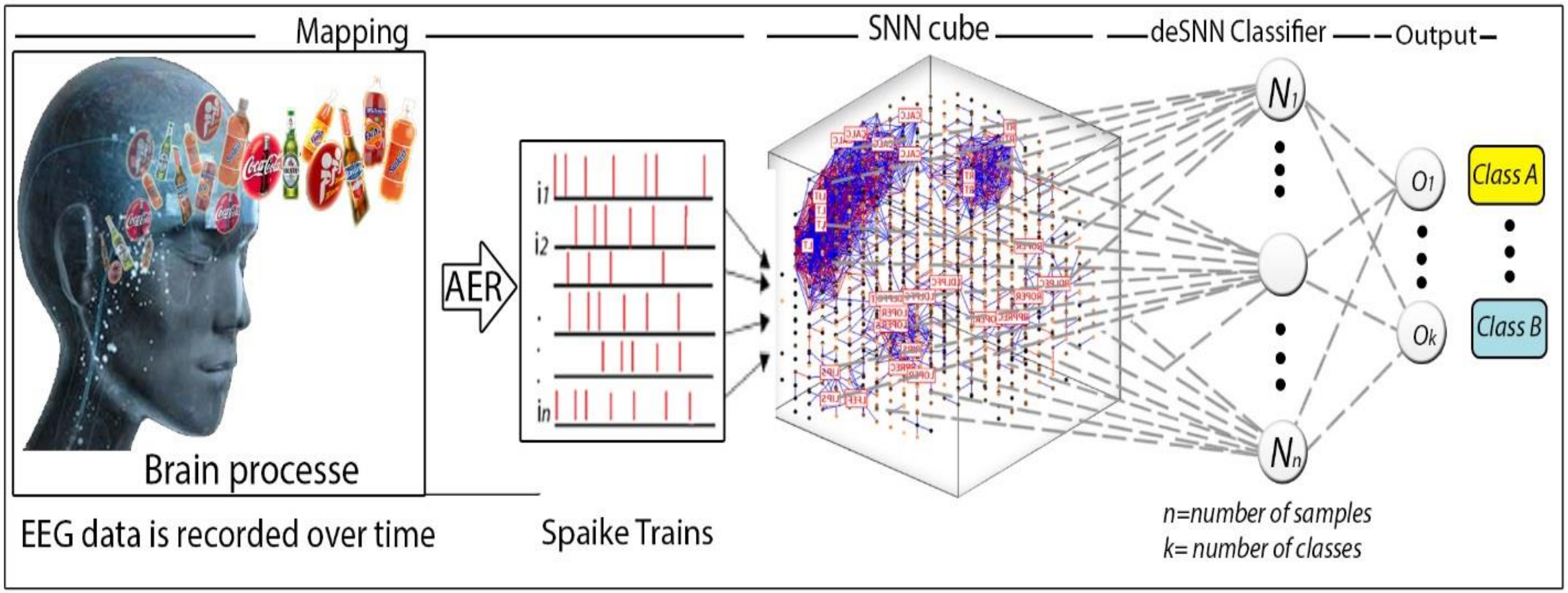
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.



A virtual environment to control a quadrotor using EEG signals.

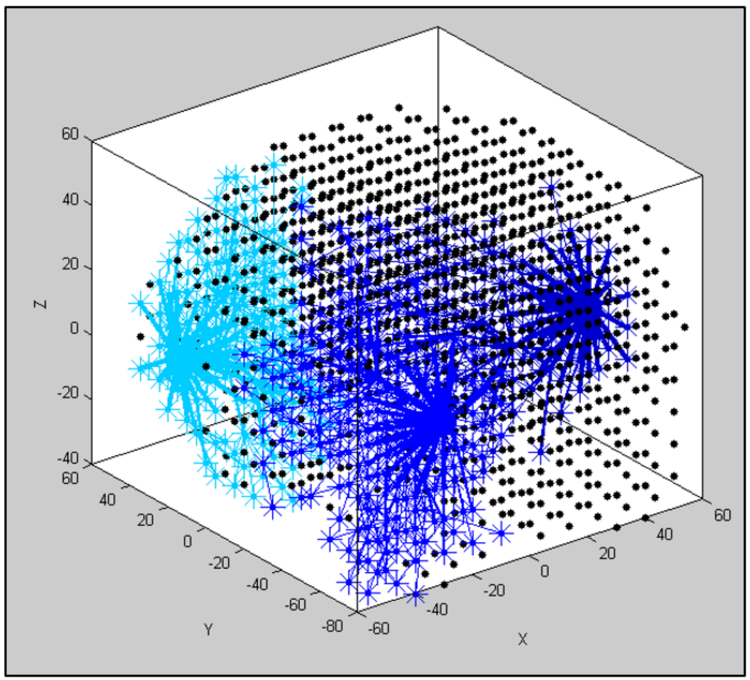
A virtual environment (3D) using Oculus rift DK2 to move in an environment using EEG signals.

EEG-based study of human decision making for neuroeconomics and neuromarketing

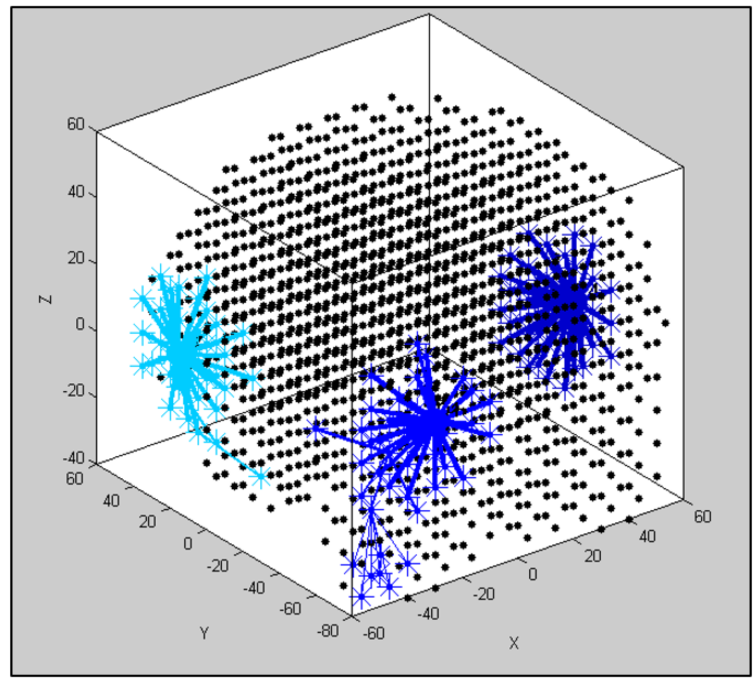


The brain functional pathways captured after the NeuCube is trained with EEG data for only 3 EEG channels (F7, O1, and T4) against Familiar and Unfamiliar Marketing Stimuli.

(With Zohreh Gholami)



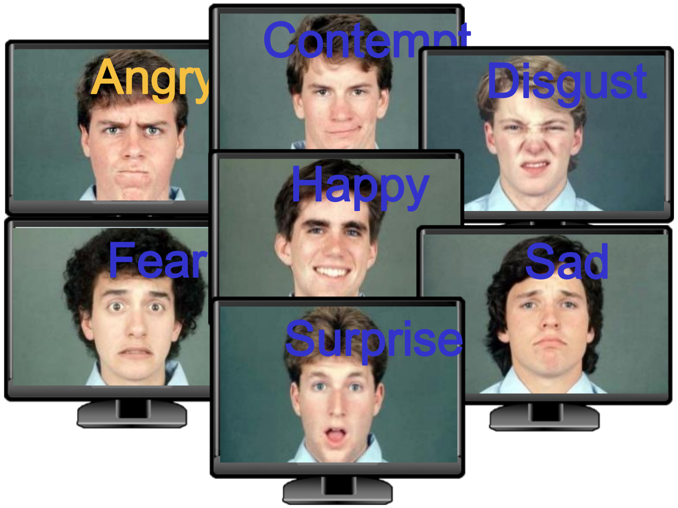
(a) Brain information pathways against Fam

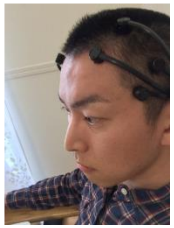


(b) Brain information pathways against UnFam

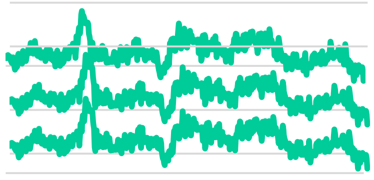
Human emotion recognition
(with Dr H.Kawano, KIT, Japan)

Facial Expression Perception Task

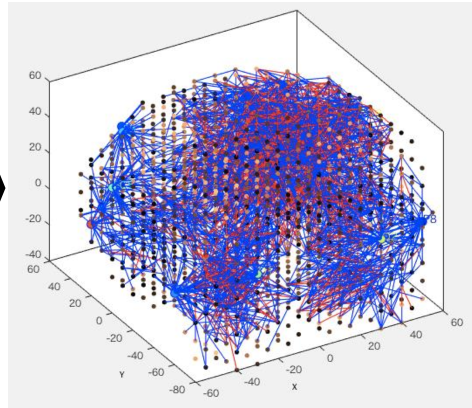




14ch EEG



94.3 %

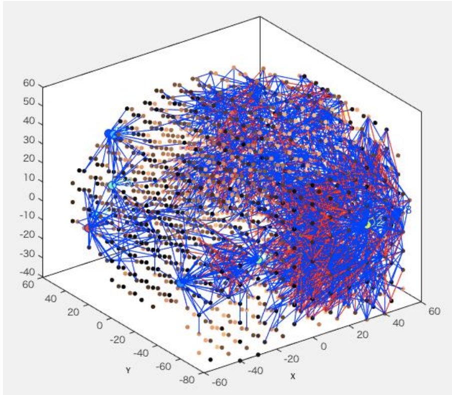


Face Expression Production Task

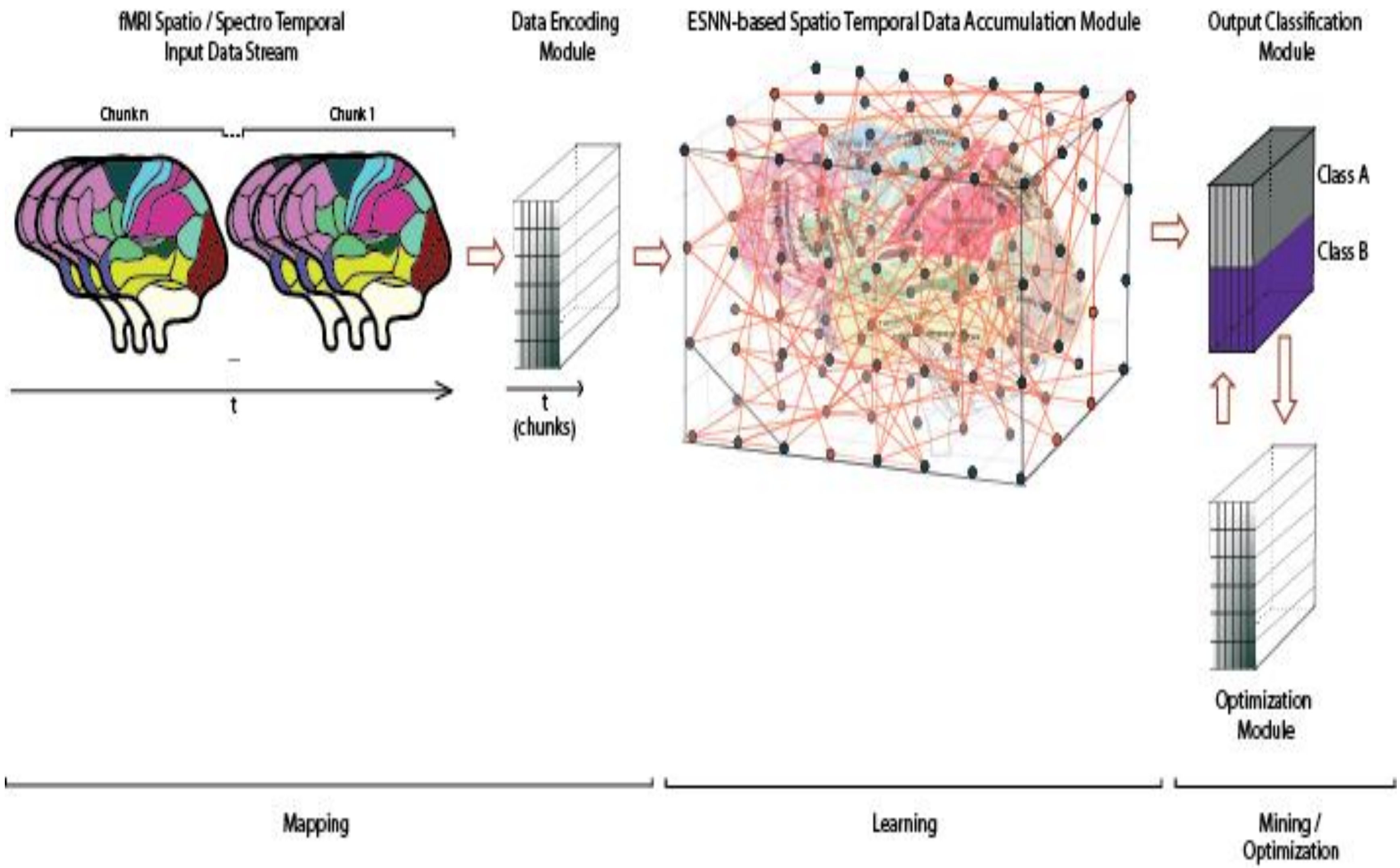
14ch EEG

97.1 %

NeuCube

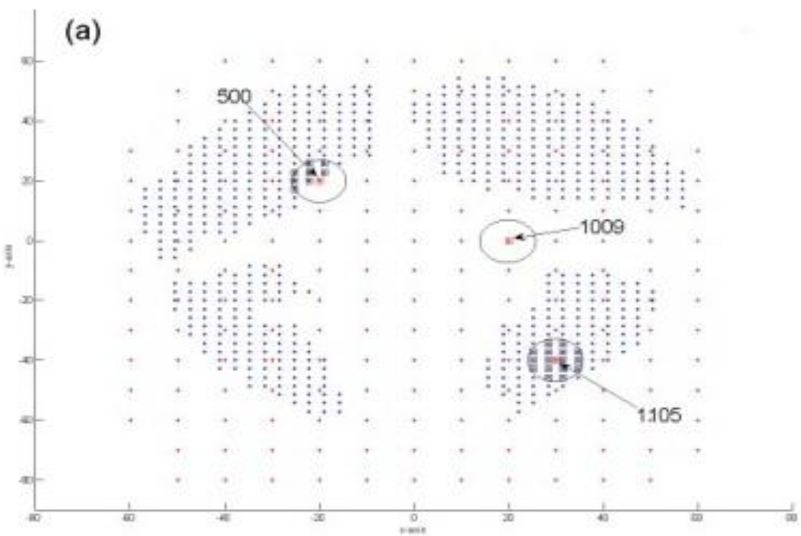


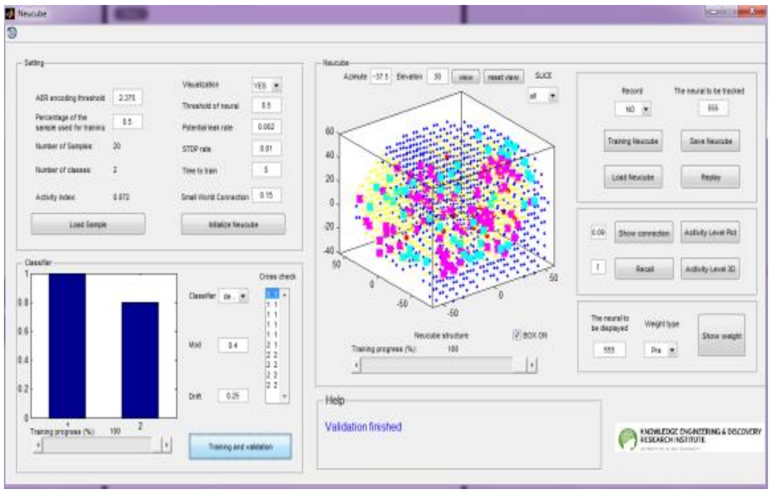
Modelling fMRI data



Classification of fMRI data

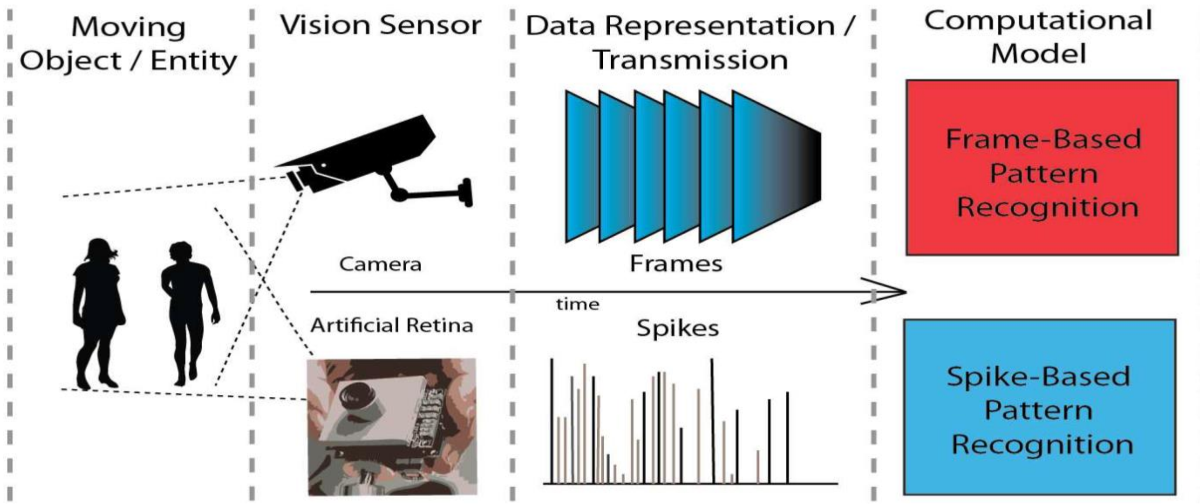
(with N.Murli, B. Handaga, ICONIP 2014, Kuching, Malaysia)

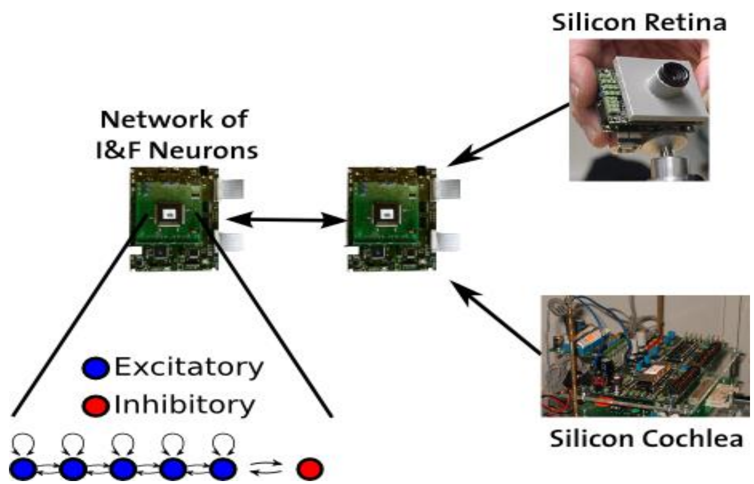




Method / Subject	SVM	MLP	NEUCUBE[B]
04799	50(20,80)	35(30,40)	90(100,80)
04820	40(30,50)	75(80,70)	90(80,100)
04847	45(60,30)	65(70,60)	90(100,80)
05675	60(40,80)	30(20,40)	80(100,60)
05680	40(70,10)	50(40,60)	90(80,100)
05710	55(60,50)	50(50,50)	90(100,80)

9. Audio-/visual information processing and moving object recognition





Fast multisensory pattern recognition from moving objects

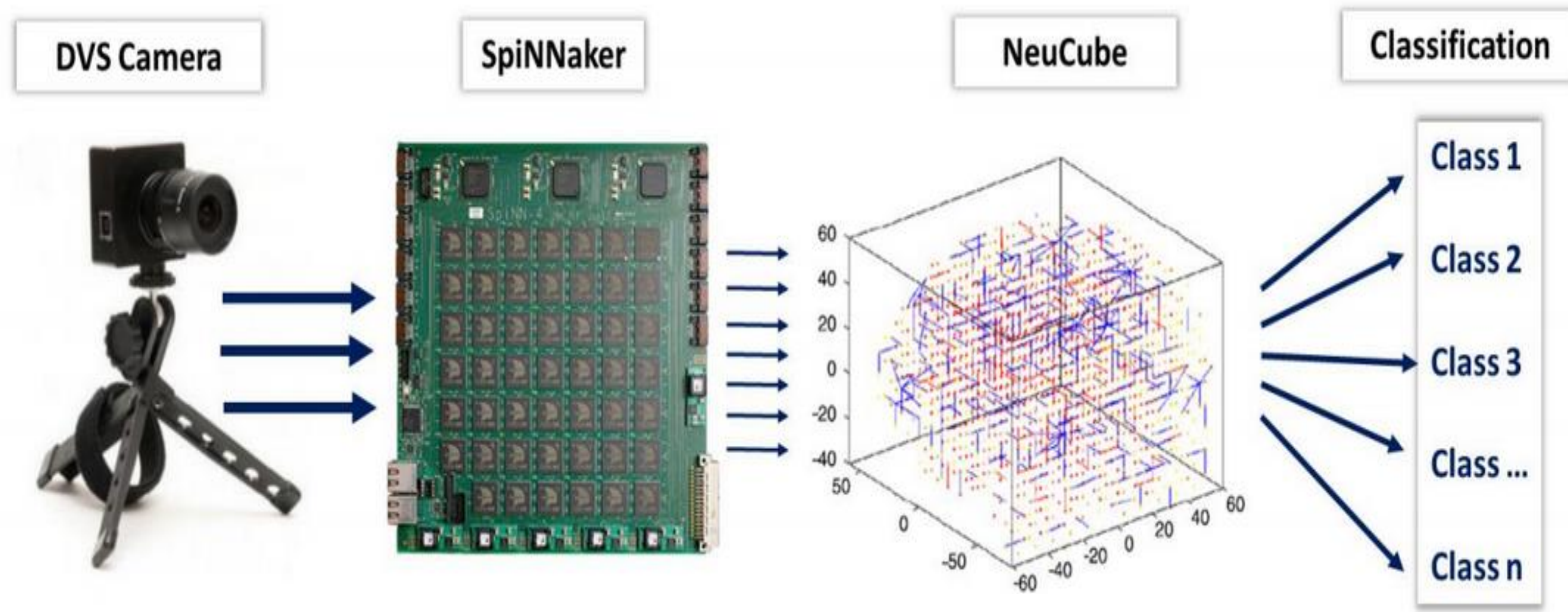
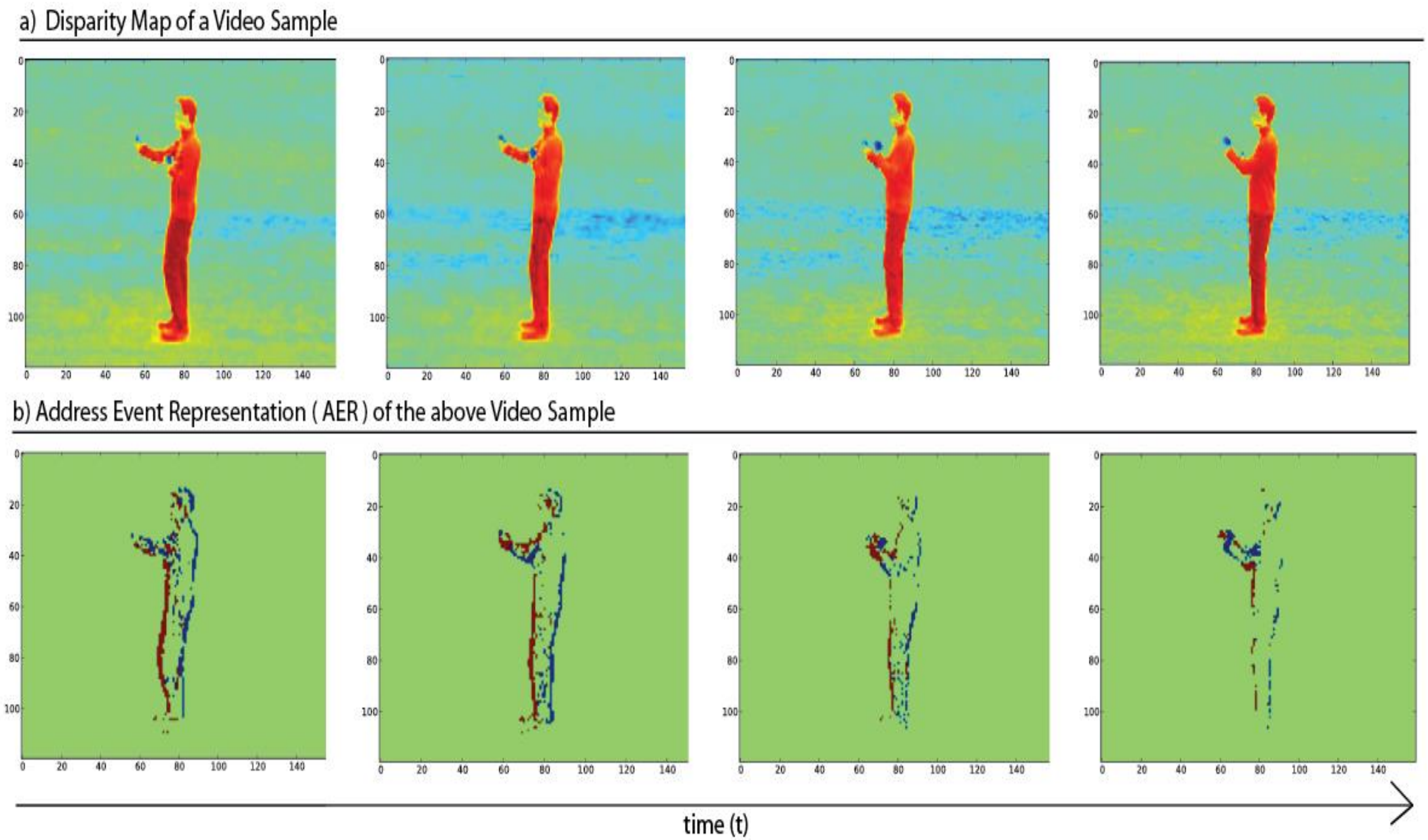


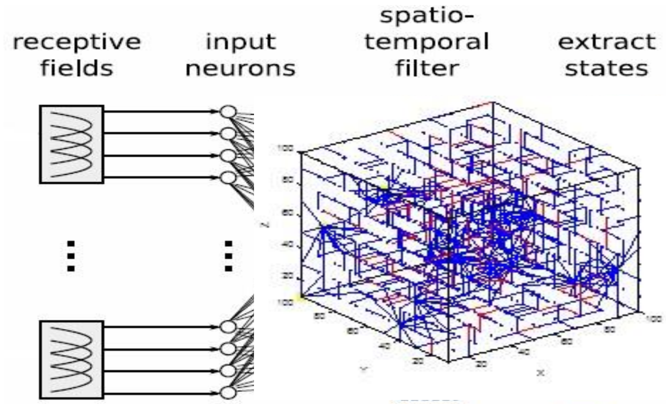
Fig.1. The architecture of the proposed DVS-NeuCube system

Example: Human movement recognition using TBE



NeuCube modelling of individual aging process

(with F. Alfi)



Classifier (SNN)

Output Class

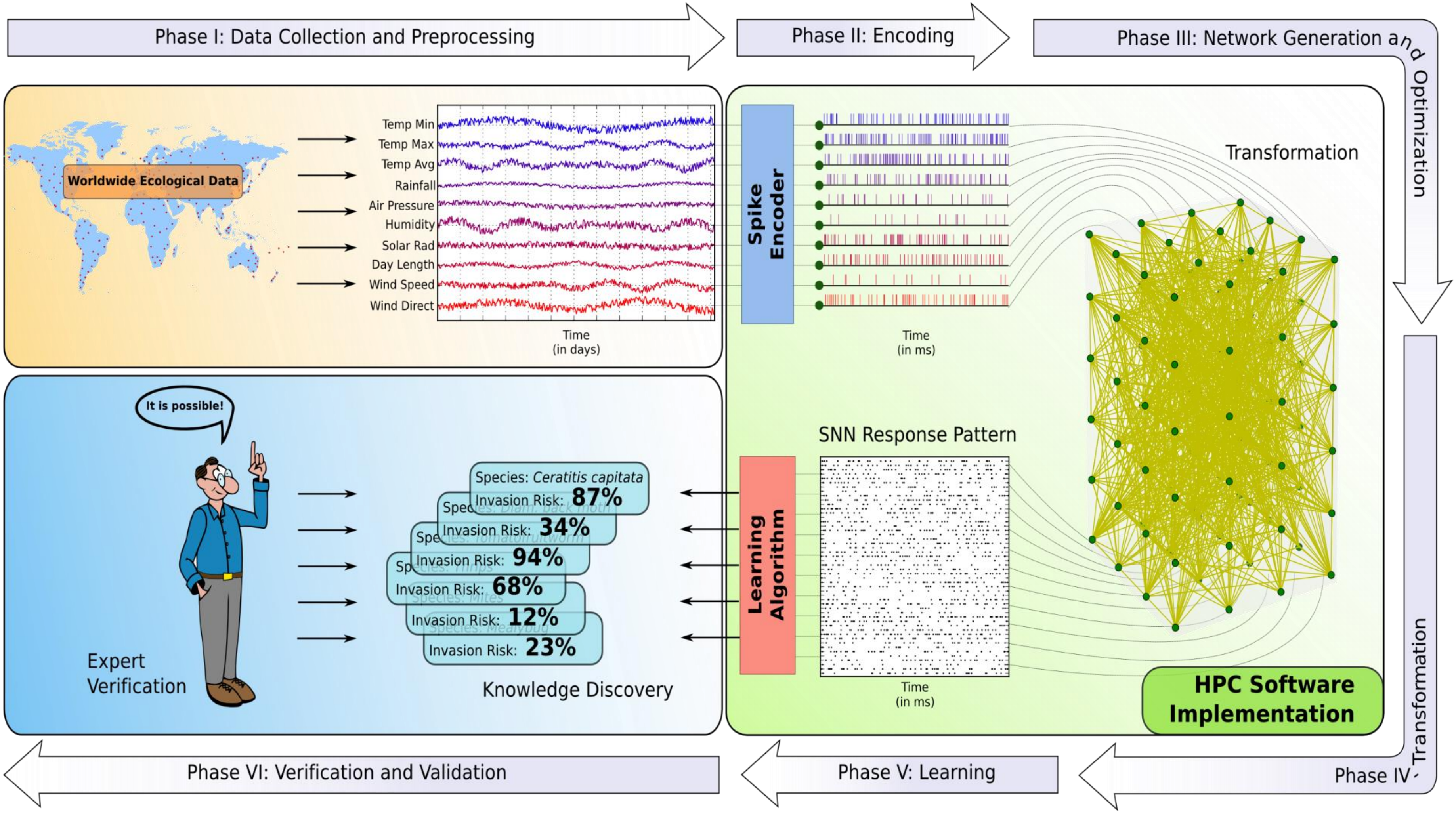
Facial temporal data is encoded into spikes

A spatio-temporal model of aging is developed

Age classification

10. Ecological and Environmental data

Example: Predicting the establishment of harmful species based on temporal climate data streams



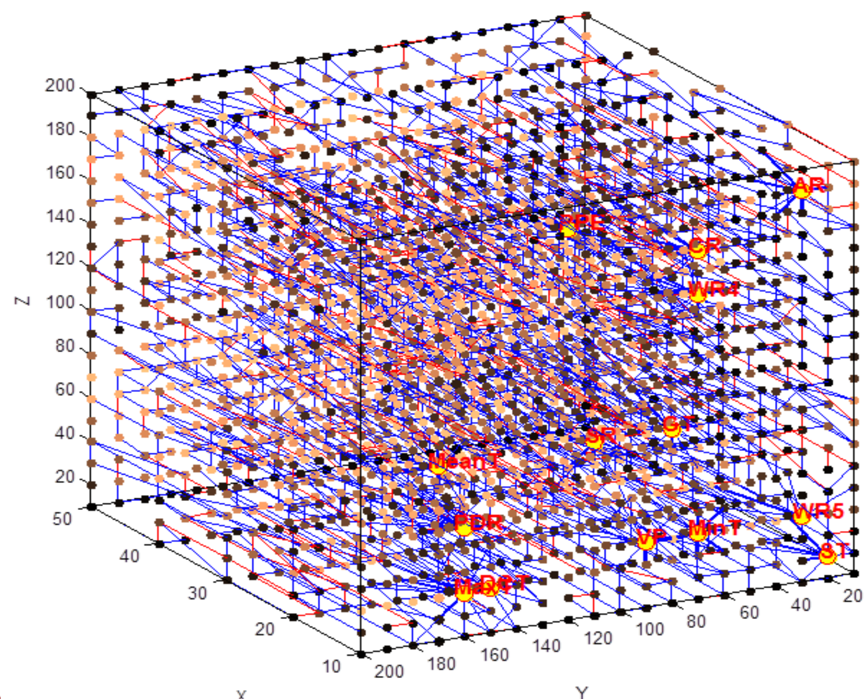
Example: Early prediction of Aphids population

(***E. Tu,*** *N. Kasabov,* ***M. Othman****, Y. Li, S. Worner, J. Yang, Z. Jia, WCCI 2014, Beijing)*

- Aphids data from NZ: 14 climate variables; size of the Aphids population at a site (large – damaging, or low – OK)
- Training a NeuCube on all 52 weeks data per year
- Testing early prediction (weeks): 52 (full) 41.6 (early) 39 (early)

	52 (full)	41.6 (early)	39 (early)
Accuracy	100%	90.91%	81.82%

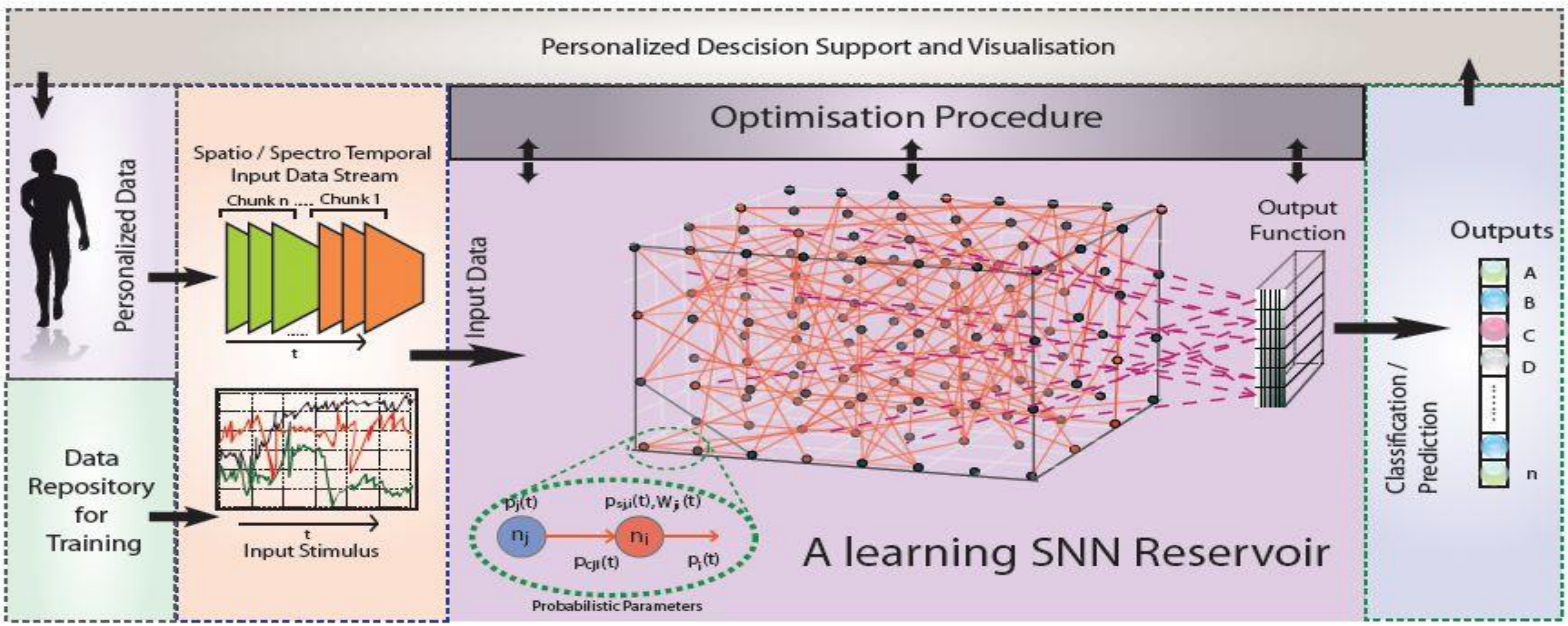
- Analysis of the Cube for a better understanding of the interaction and importance of variables:



Personalised predictive systems

(*Kasabov, et al, Evolving Spiking Neural Networks for Personalised Modelling of Spatio-Temporal Data and Early Prediction of Events: A Case Study on Stroke. Neurocomputing, 2014).*

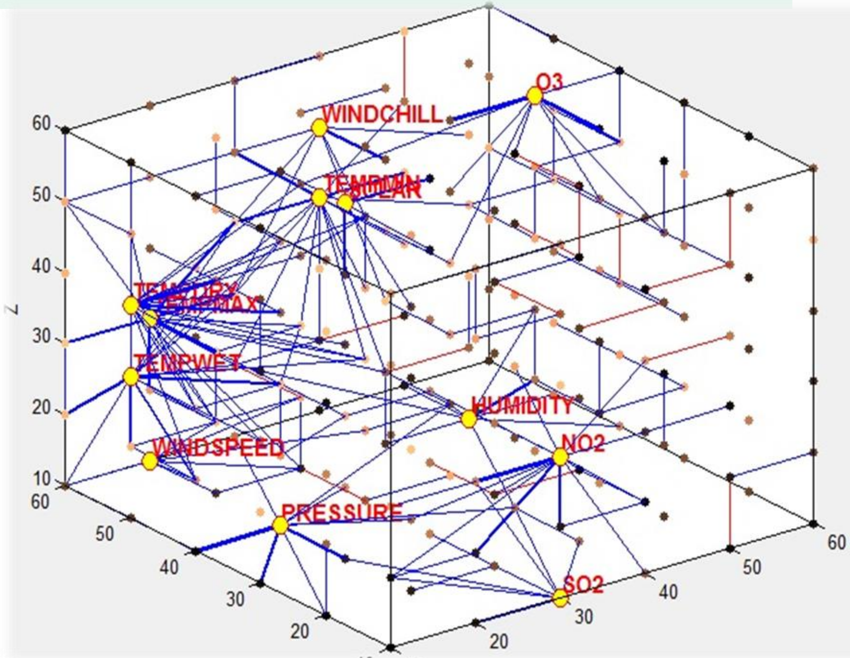
1. For an individual X a neighbourhood of samples is collected based on static variables
2. A NeuCube model is created from the (spatio) temporal data of the neighboring individuals to predict the output for the individual X

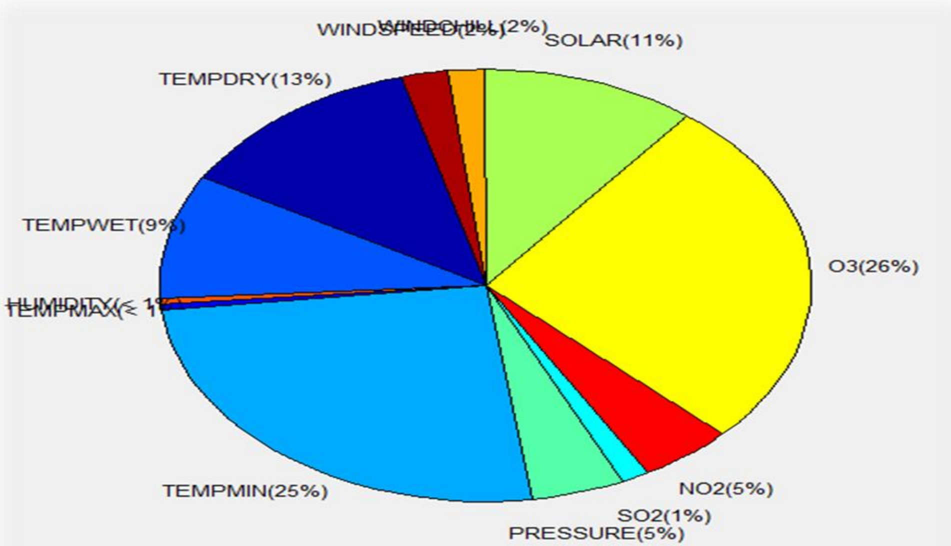


Personalised modelling and individual health risk prediction based on **multisensory data** in a real time: The case on stroke

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

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



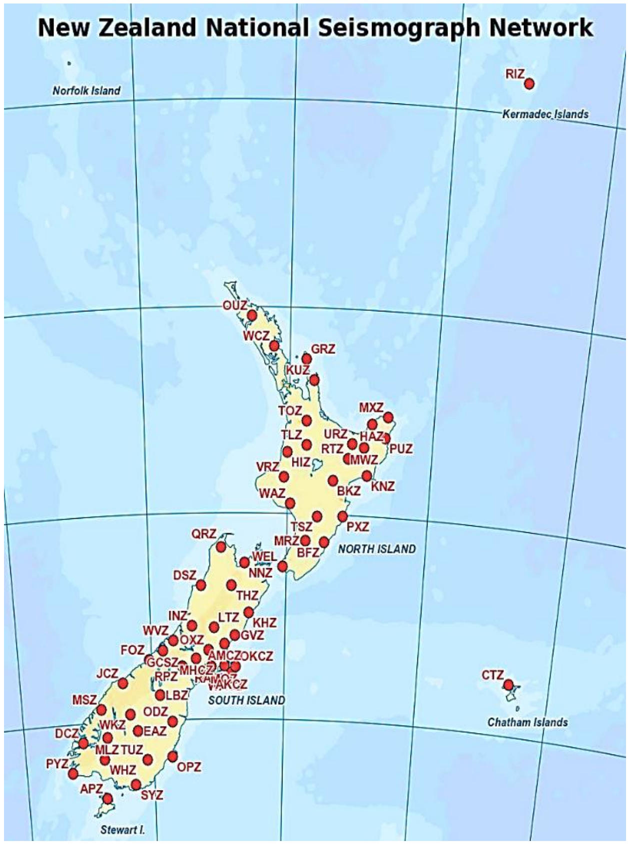


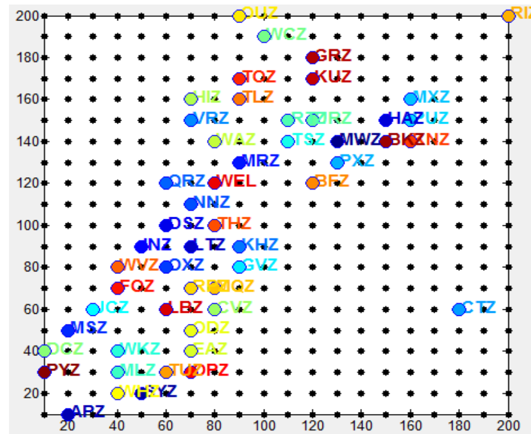
(d) Neuron proportion based on spike transmission

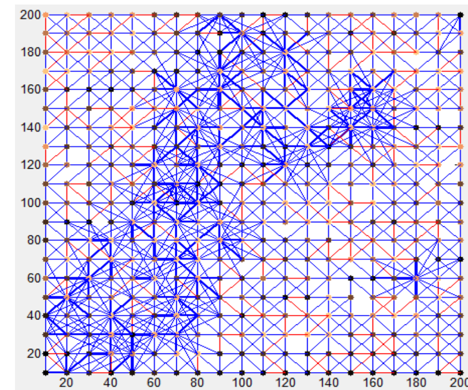
- SNN achieve better accuracy
- SNN predict stroke much earlier than other methods
- New information found about the predictive relationship of variables

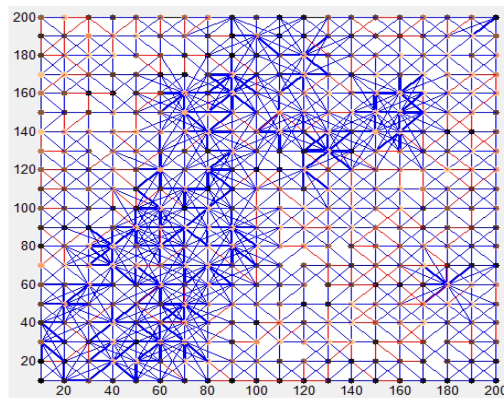
Seismic data modelling for earthquake prediction

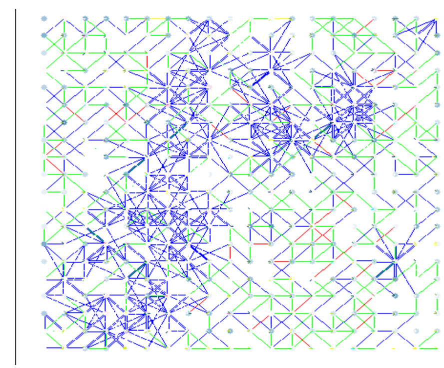
(with Reggio Hartono)











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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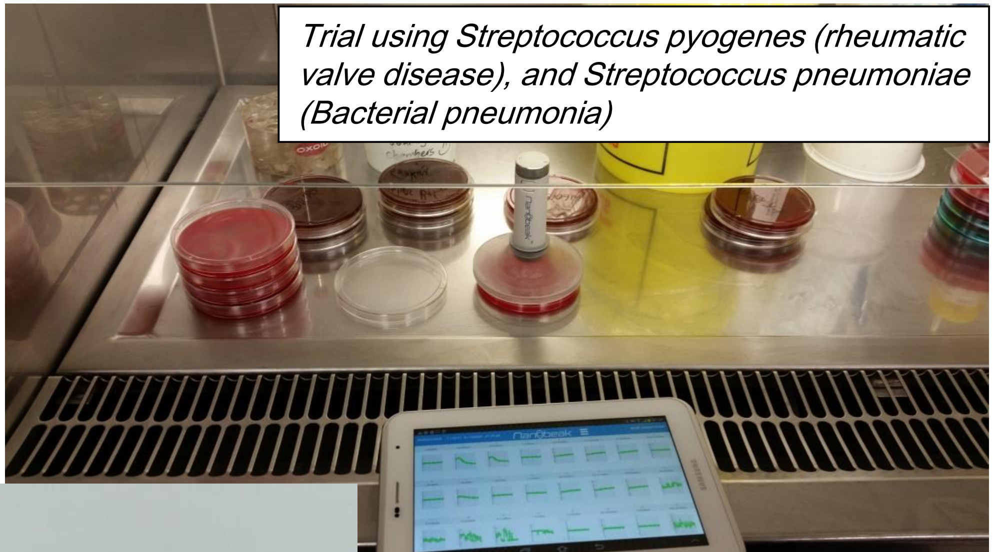
11. Bioinformatics

Personalised modelling for risk of CVD estimation based on gas and breath sensor data (with Vivienne Breen, Dr Patrick Gladding)

Trial using Streptococcus pyogenes (rheumatic valve disease), and Streptococcus pneumoniae (Bacterial pneumonia)



Research Correspondence

Single Exhaled Breath Metabolomic Analysis Identifies Unique Breathprint in Patients With Acute Decompensated Heart Failure

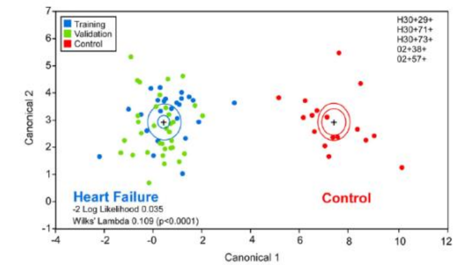


Figure 1 Canonical Discriminant Analysis: ADHF Versus Non-HF Controls

Canonical discriminant analysis using 5 selected mass scanning ion peaks was performed in a training cohort of 25 acute decompensated heart failure (ADHF) subjects **(blue)** and 16 controls **(red)**. This ADHF "breathprint" was then used to classify an independent validation cohort of 36 ADHF subjects **(green)** with no misclassifications.

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April 2, 2013:1461–8

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Electronic nose detects heart failure from exhaled breath

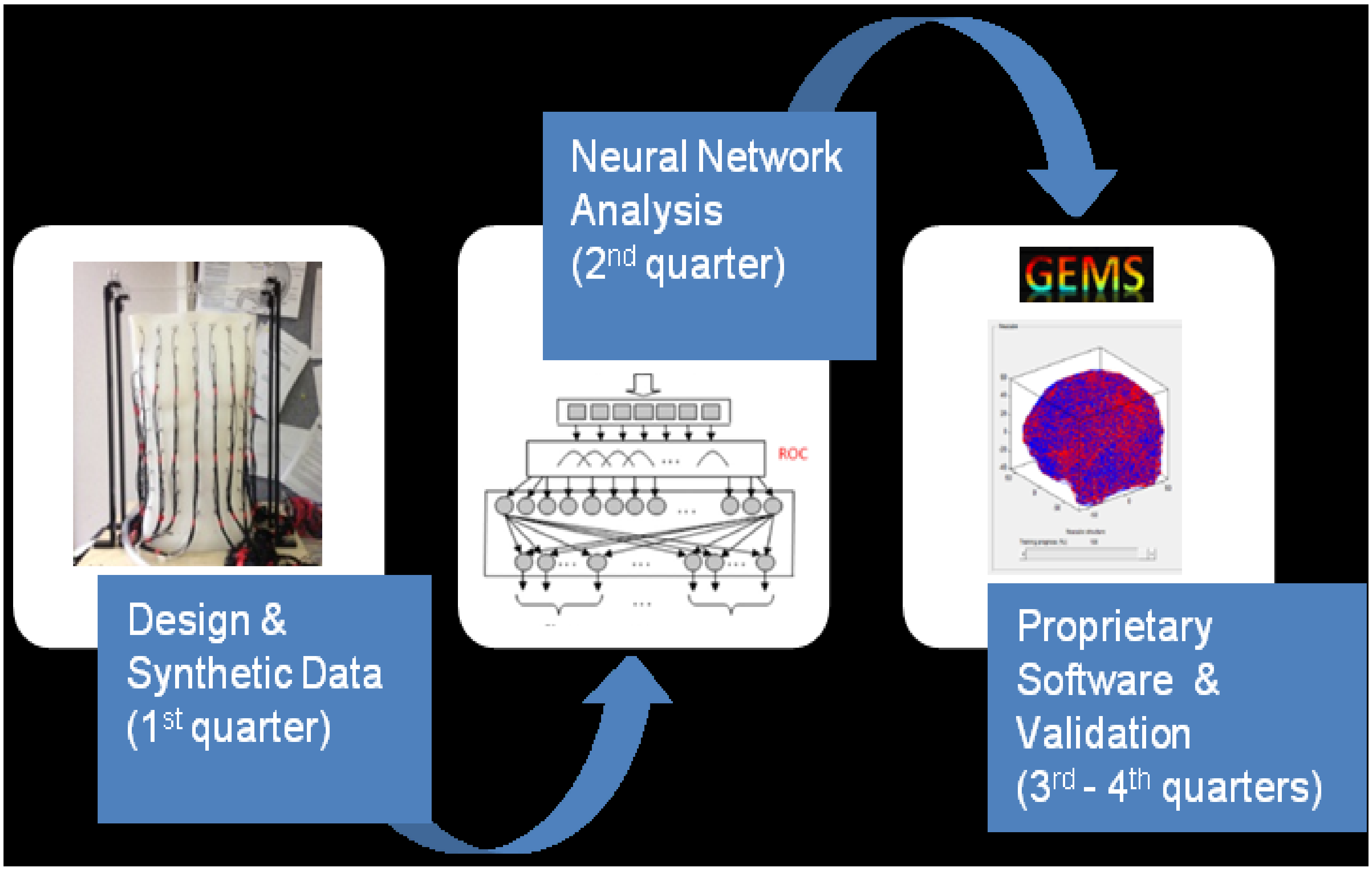
Witt K[1], Fischer C[1], Reulecke S[1], Kechagias V[2], Surber R[2], Figulla HR[2], Voss A[1]

[1]Department of Medical Engineering and Biotechnology, University of Applied Sciences Jena, Jena, Germany
[2]University Hospital Jena, Department of Internal Medicine I, Jena, Germany

andreas.voss@fh-jena.de

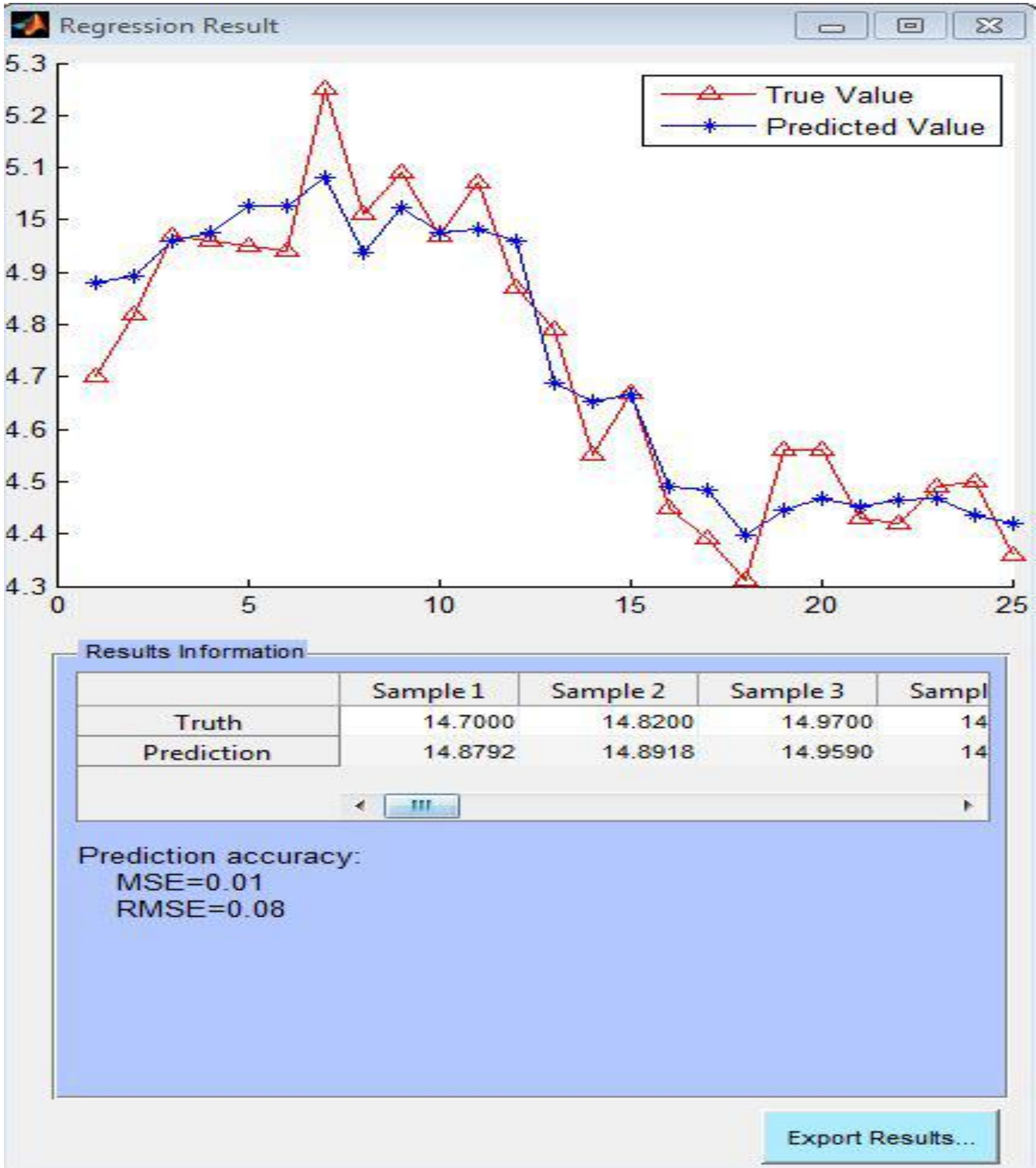
Personalised modelling for clinical electrogastrography

(with Vivienne Breen, Dr Peng Du – MedTech CoRE)



12. Predictive modelling on financial and business streaming data
(NeuCube Manual)

- A demo dataset for regression analysis.
- Available from: www.kedri.aut.ac.nz/neucube/ data>share_price folder.
- Training/testing uses 50 samples;
- Each sample consists of 100 timed sequences of daily closing price of 6 different shares! (Appel, Google, Intel; Microsoft, Yahoo, NASDAQ)
- The target values are the closing price of NASDAQ at the next day.



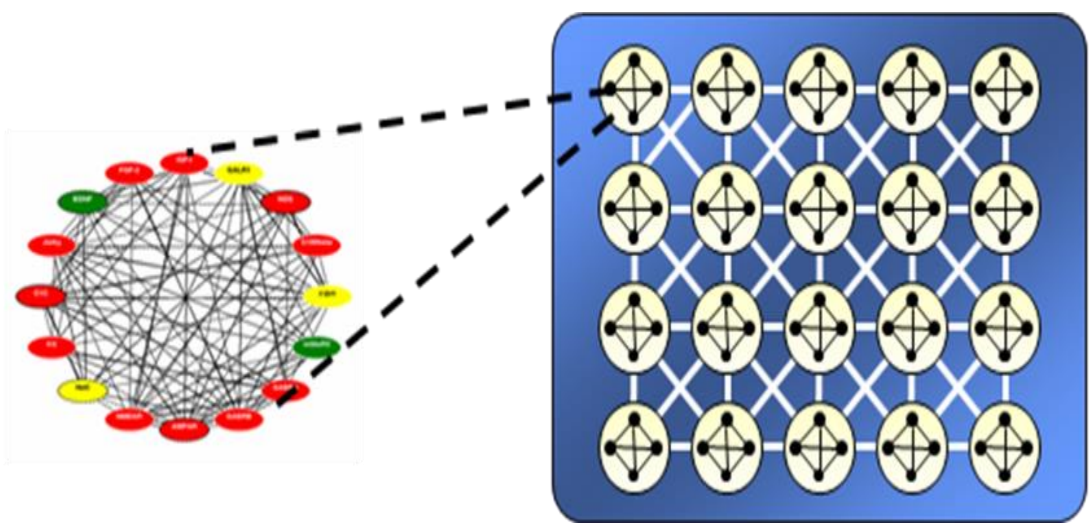
Part IV: Advanced Topics

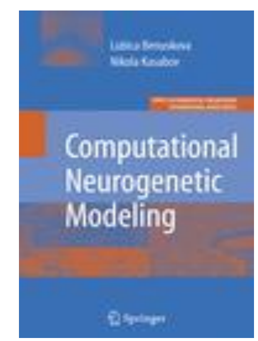
13. Computational Neuro-Genetic Modelling (CNGM)

- Benuskova and Kasabov (2007)

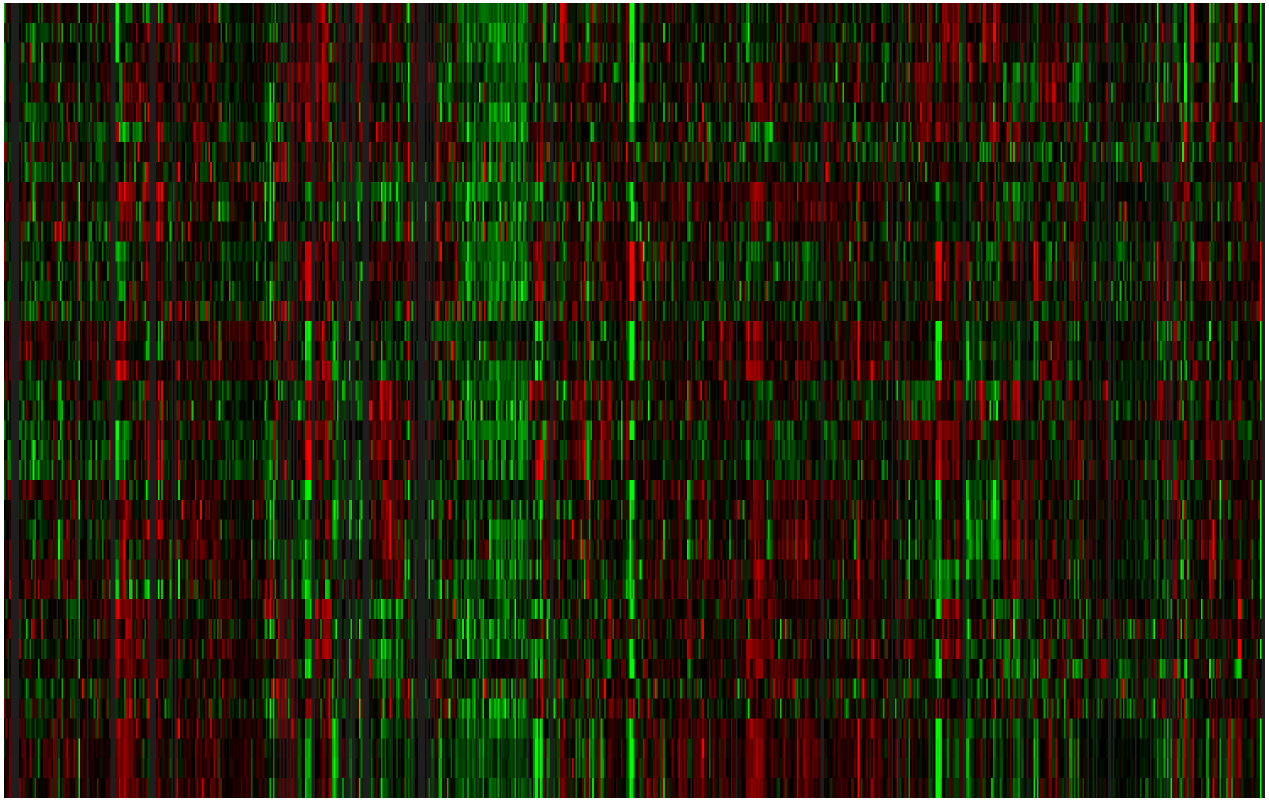
SNN that incorporate a gene regulatory network (GRN) as a dynamic parameter systems to capture dynamic interaction of genes (parameters) related to neuronal activities of the SNN.

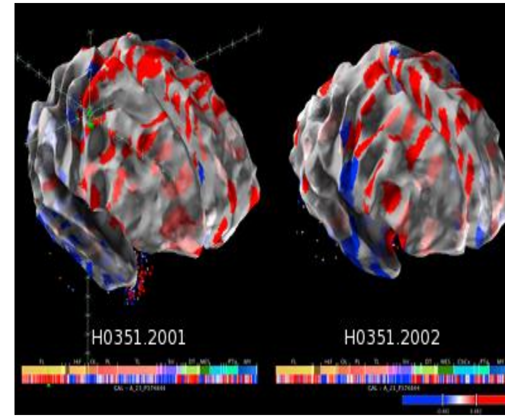
- Functions of neurons and neural networks are influenced by internal networks of interacting genes and proteins forming an abstract GRN model.
- The GRN and the SNN function at different time scales.





Neurogenetic STBD: The Allen Brain Institute Map (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)

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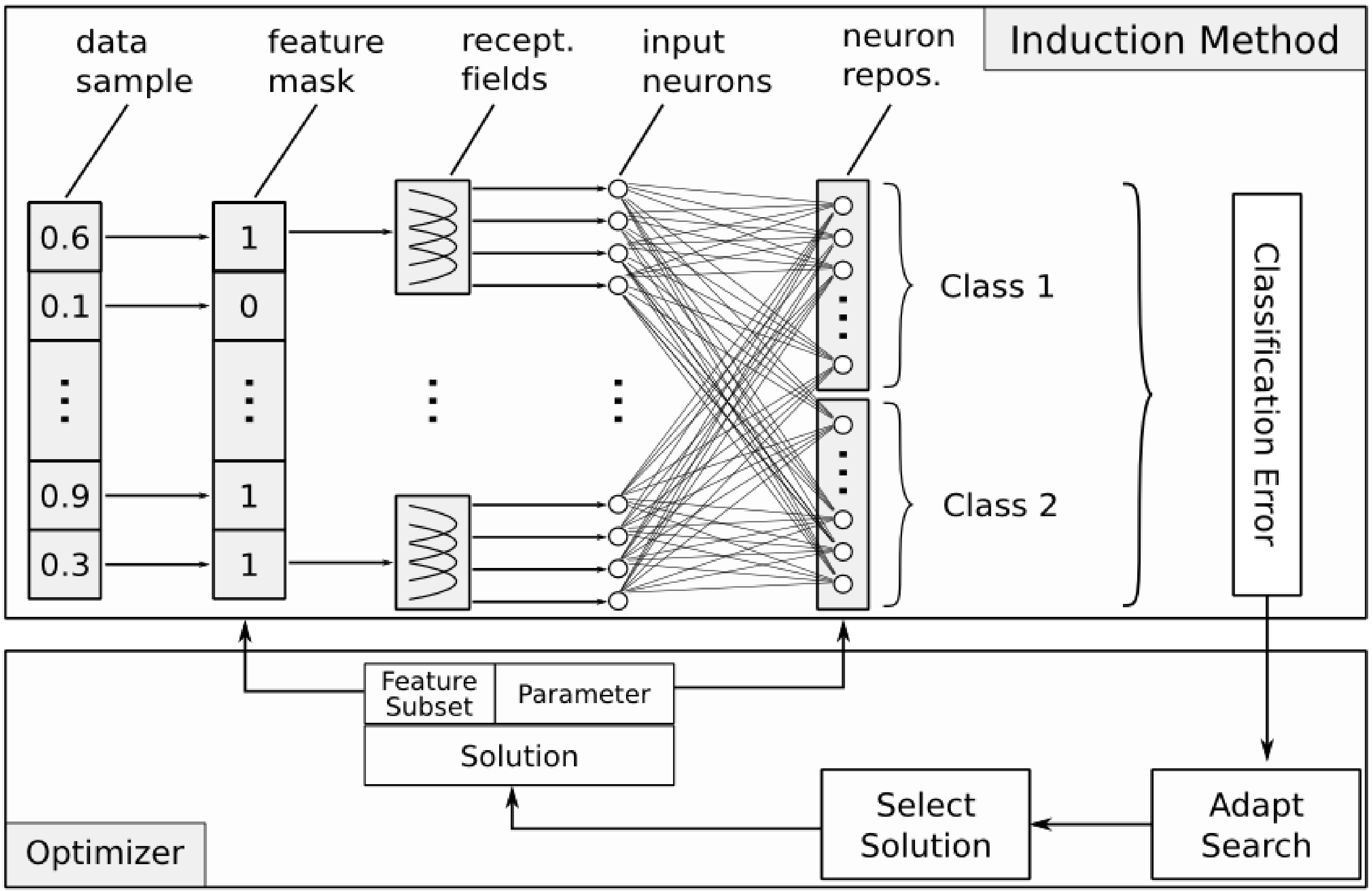
14. Quantum-inspired optimisation of eSNN

(Kasabov, 2007-2008; S.Schliebs, M.Defoin-Platel and N.Kasabov, 2008; Haza Nuzly, 2010))



Quantum Inspired Optimisation Methods

- Quantum principles: superposition; entanglement, interference, parallelism
  - Quantum bits (qu-bits)

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \qquad\qquad |\alpha|^2 + |\beta|^2 = 1$$

- - Quantum vectors (qu-vectors)

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

- Quantum gates

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

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

15. Discussions and Future Directions

Advantages of SNN:

- Universal computational mechanism
- Extendable, evolvable models, with more data and biologically related knowledge as they become available (e.g. genes, quantum information)
- Can learn deep spatio-temporal relationships from spatio-temporal data
- Early and accurate predictive data modelling.
- Tracing processes *back* in time
- Fast and less computationally demanding (spikes are easy to compute)
- Low power consumption if realised in a neuromorphic hardware

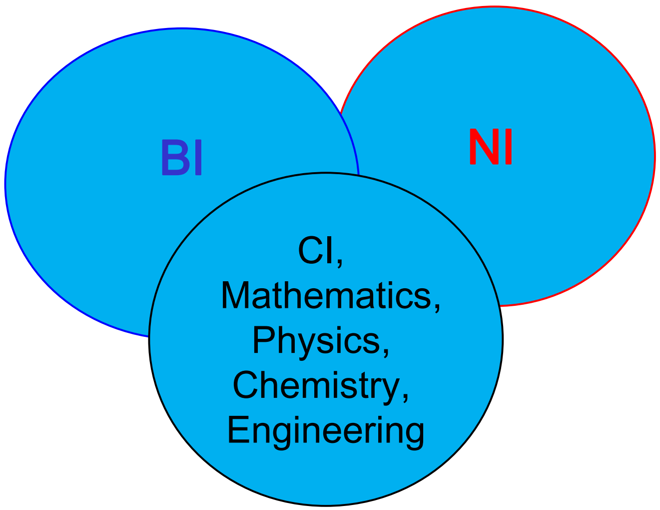
Problems and limitations of SNN

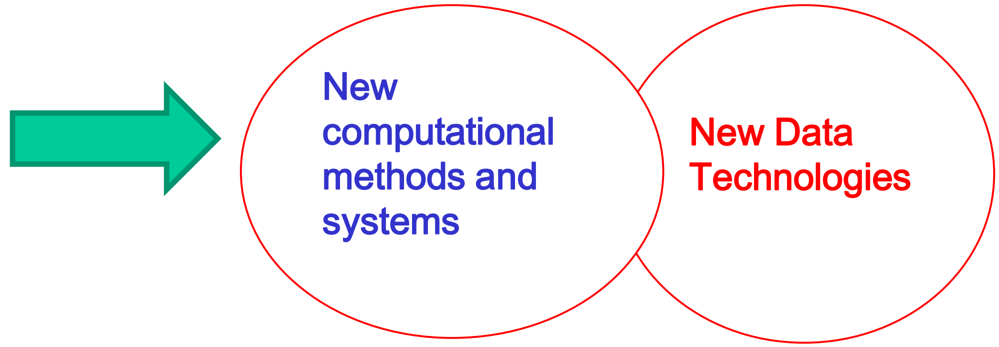
- Sensitive to parameter values
- Large number of parameters that need to be optimised
- Unknown behaviour for different types of spatio-temporal data
- No rigid theory yet, e.g. How deep is the learning in the 3D SNNc?

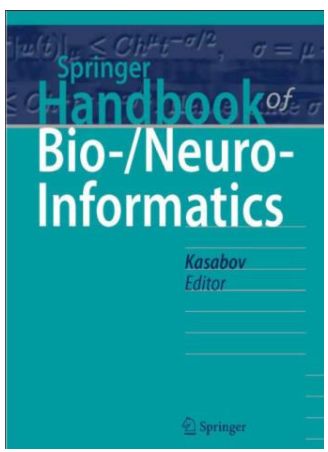
Comparison between statistical methods, second generation of ANN (e.g. MLP, Convolutional NN) and SNN

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







- Modelling emergence of symbolic representation
- Multimodal and multi-model SNN systems
- Better on-line learning in real time

- Real time event prediction systems
- Embedded systems
- Neurological prosthetics

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