ICONIP 2012, Doha, Qatar, November 2012

Mapping, Learning and Mining of Spatiotemporal Brain Data with 3D Evolving Spiking Neurogenetic Models

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Content

1. Brain information processes and spatio-temporal brain data (STBD).

2. The challenge is ***MLM of STBD*** and why standard ML techniques failed

3. Why use spiking neural networks (SNN)

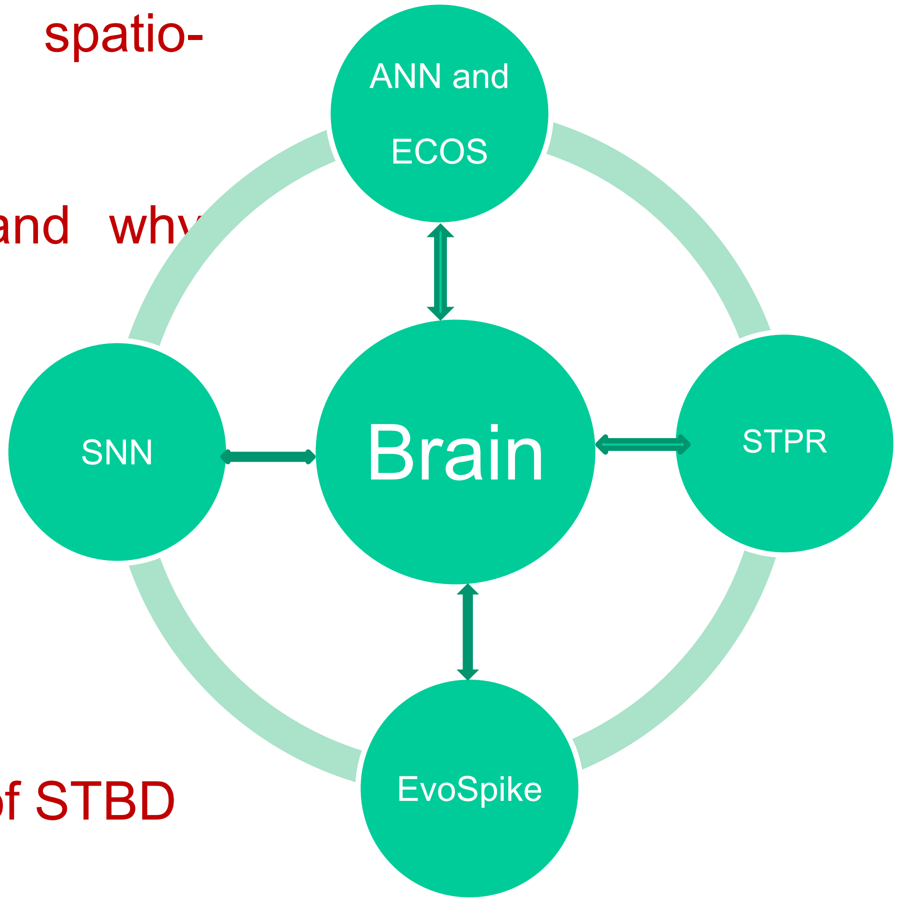
4. The EvoSpike project and the NeuCube

5. NeuCube for EEG and fMRI STBD

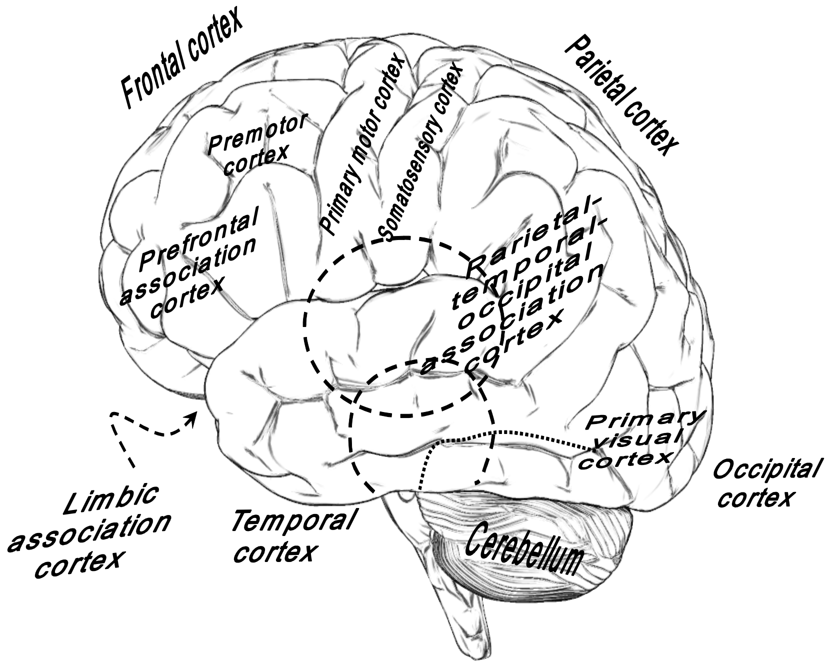
6. Computaional Neurogenetic Modelling of STBD

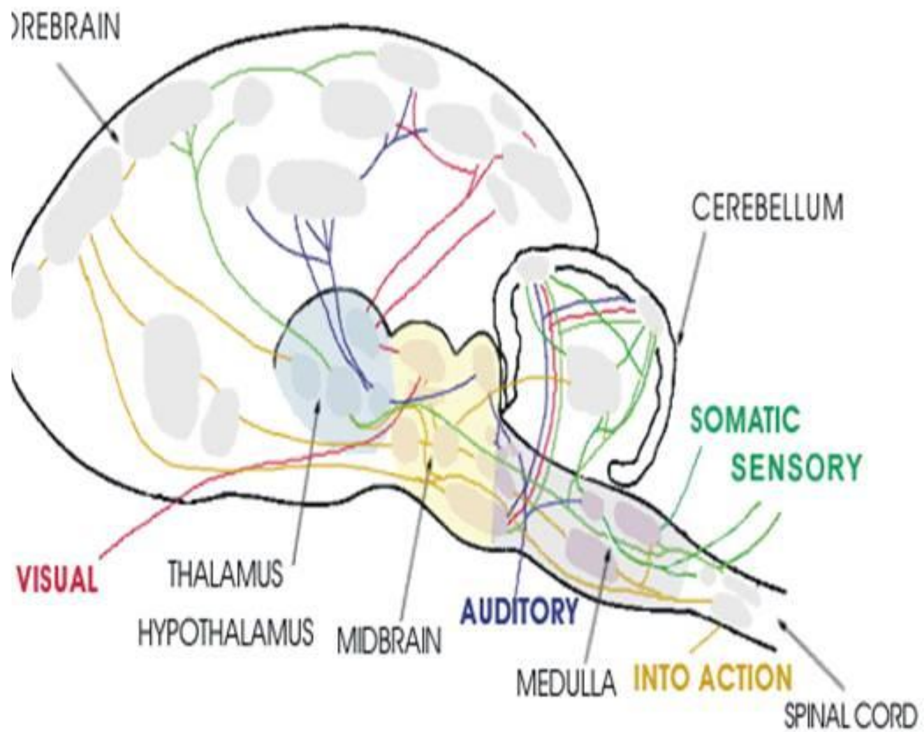
7. Optimisation of NeuCube parameters

8. Future directions

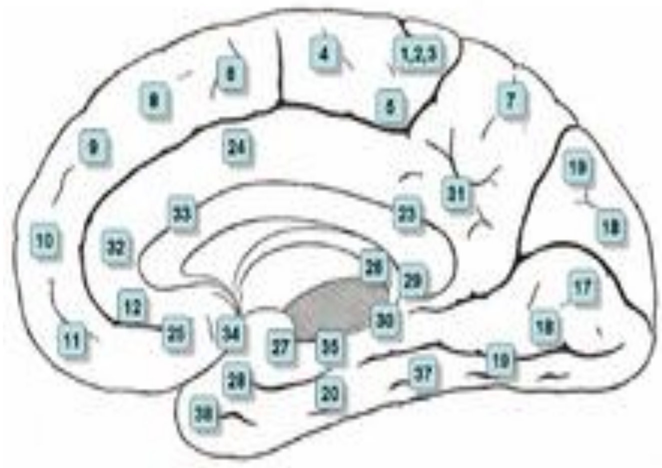


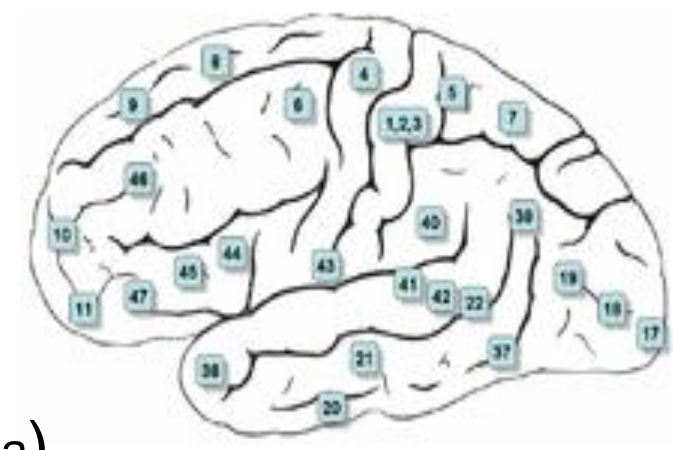
1. Brain information processes and spatio-temporal brain data (STBD)





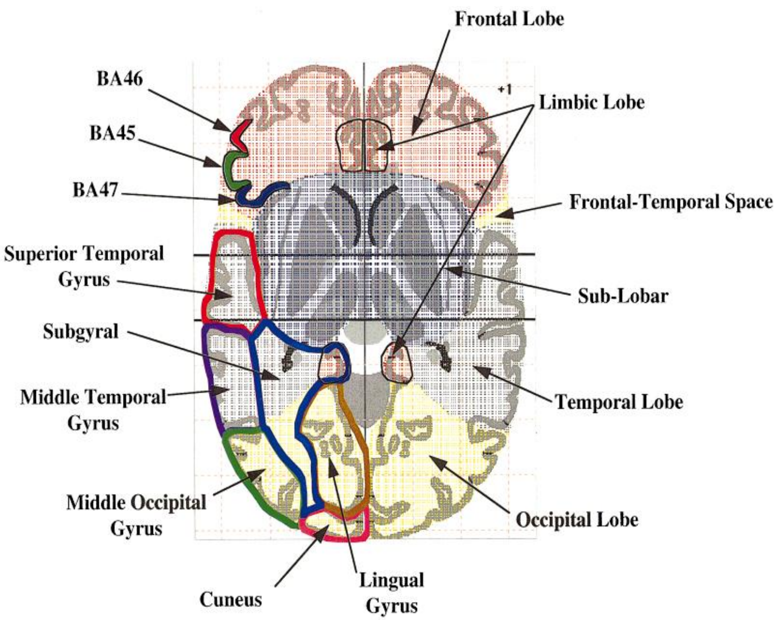
3D Brain cytoarchitectonic map: Brodmann areas (1909)

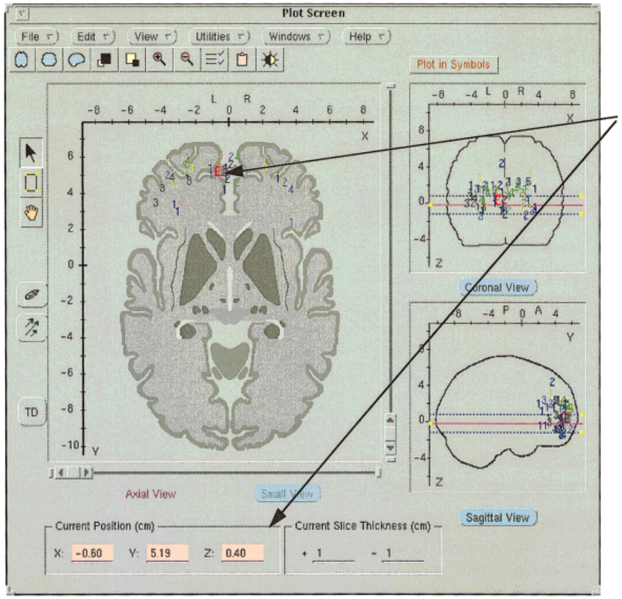




(from Wikipedia)

3D Brain Sterotaxic Coordinates: Talairach and MNI templates





Talairach Label

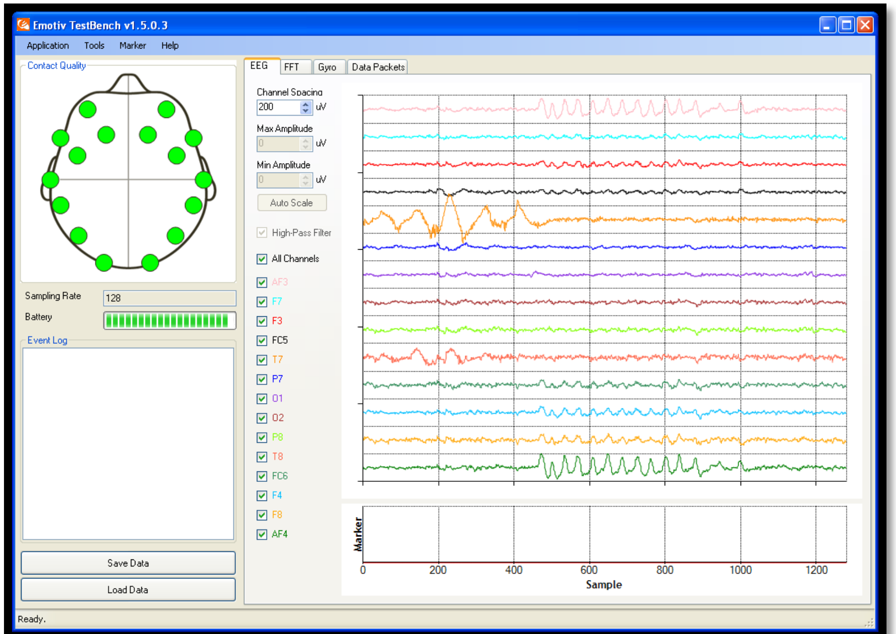
Left Cerebrum
Frontal Lobe
Medial Frontal Gyrus
Gray Matter
Brodmann area 10

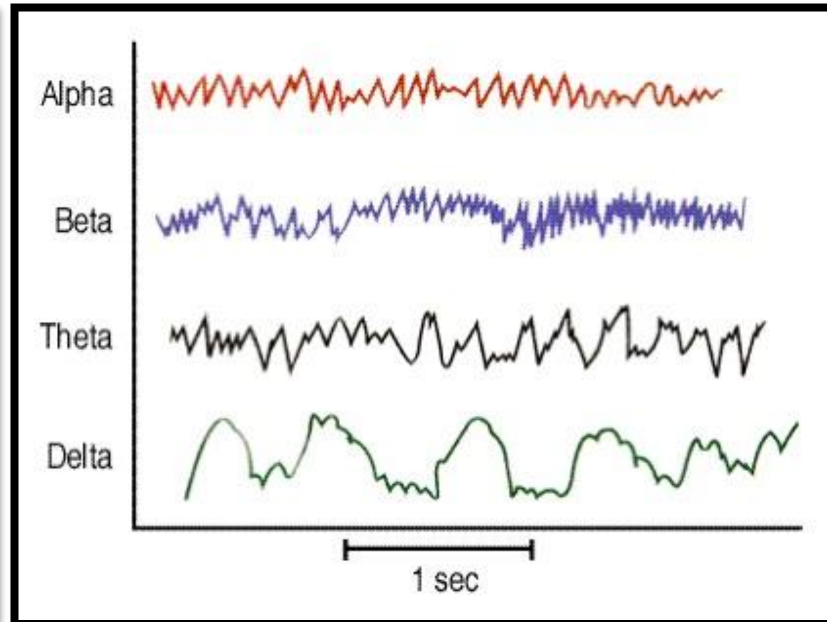
x = -6 mm
y = 52 mm
z = 4 mm

Query on Brodmann Area 10 yielded:

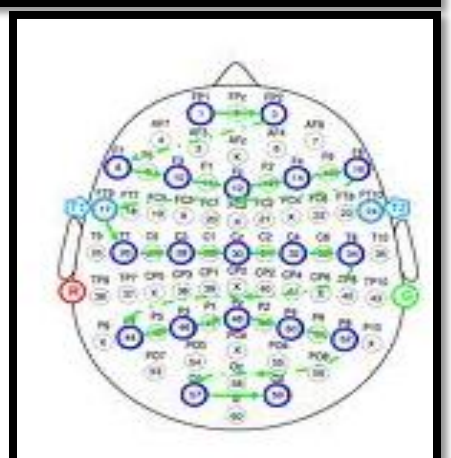
- 32 papers
- 46 experiments

Spatio-*Temporal* EEG Data



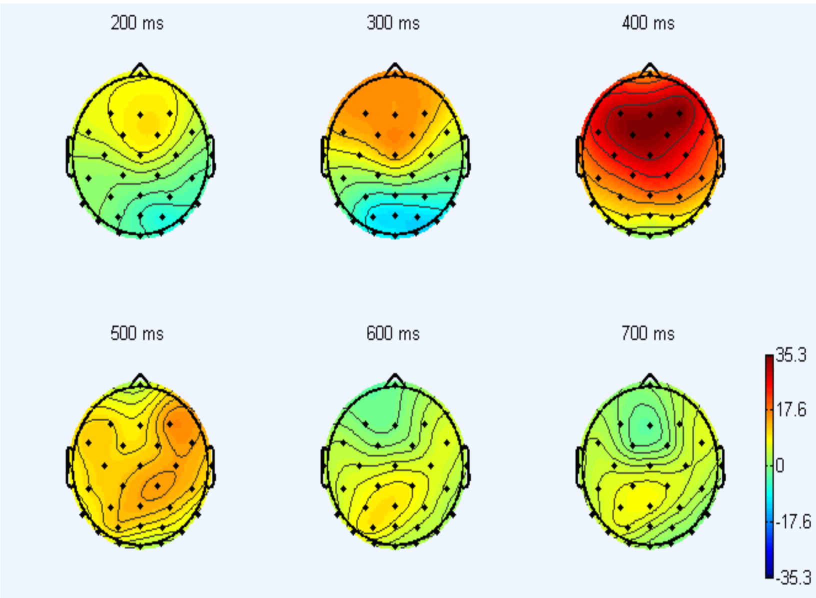


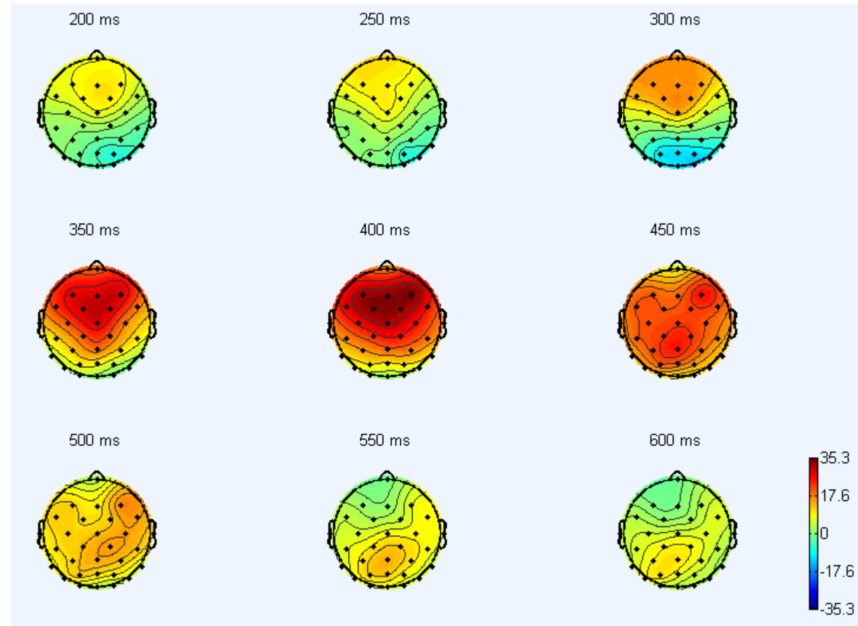
(McFarland, Anderson, MÜller, Schlögl, Krusienski , 2006)



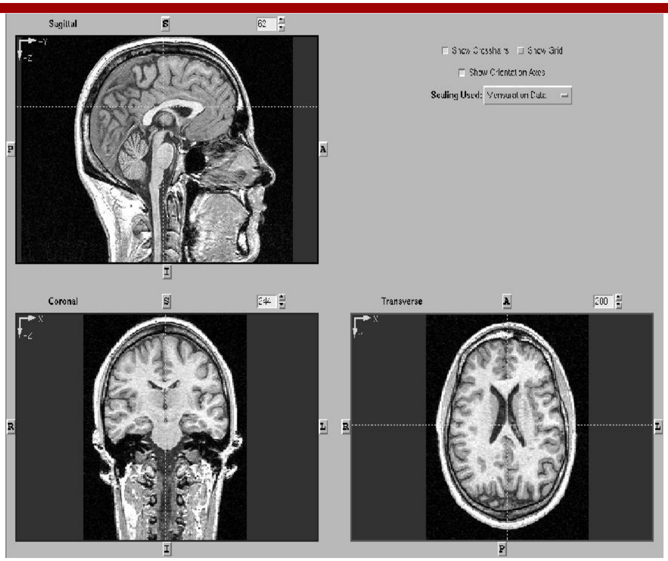
http://www.nuroshop.com

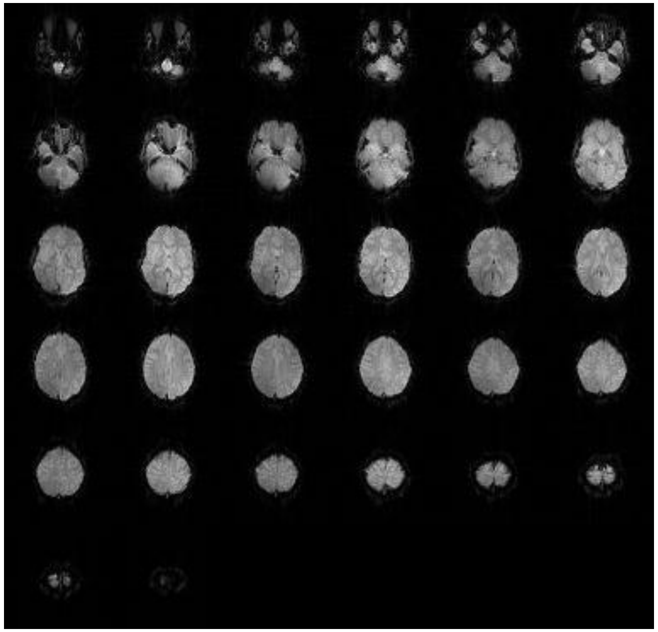
EEG signals are *indeed* spatio-temporal





Spatio-Temporal fMRI Data

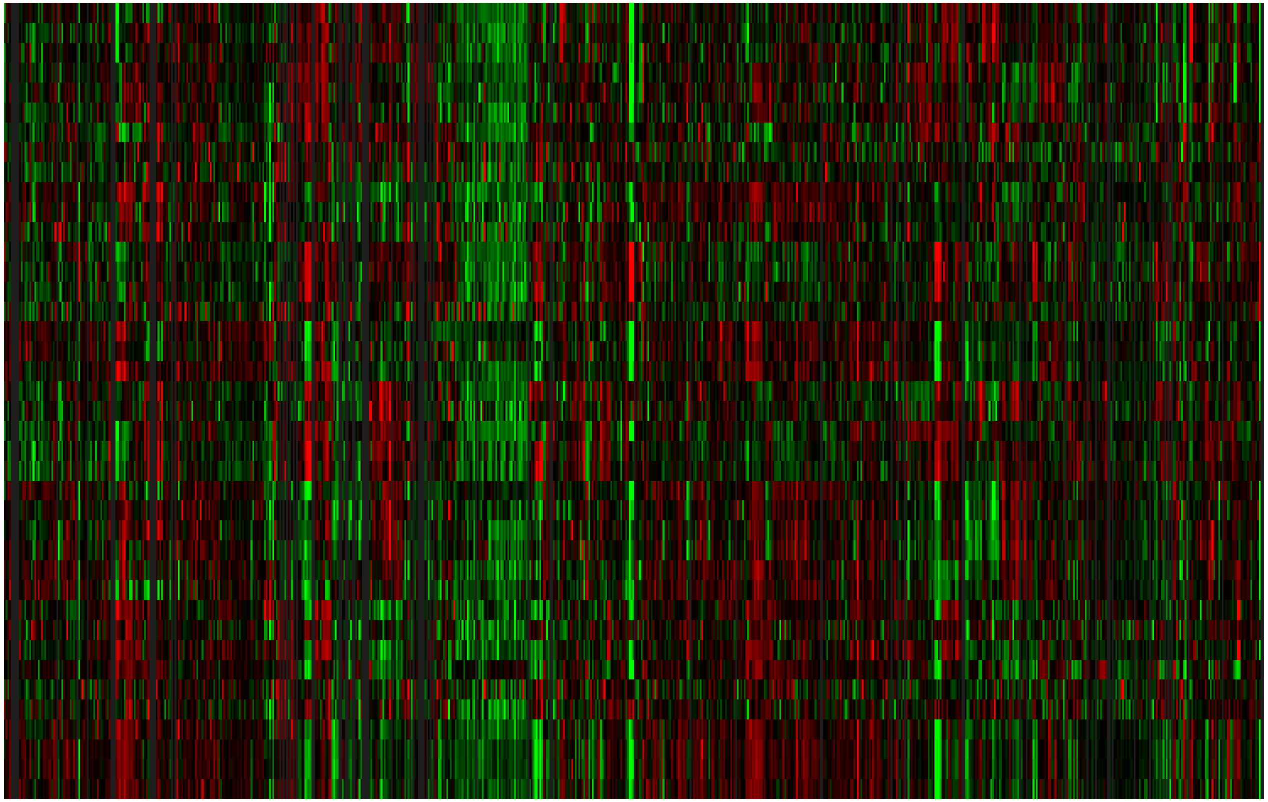


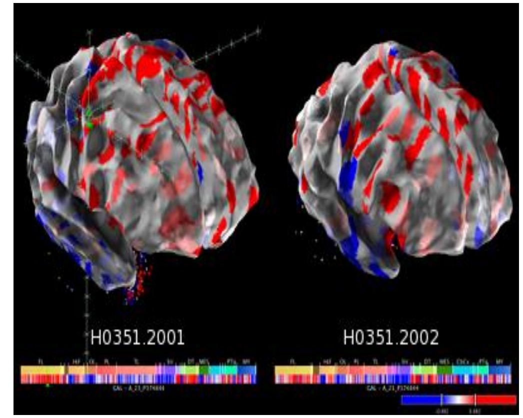


- fMRI images are taken in sequence and over time either vertically or horizontally (sagittal / coronal / axial)
- Each image in the sequence is called a slice which represents a spatial activity of the brain
- A collection of slices → a volume
- A slice is made up of voxels, (individual cube elements), which can have a spatial resolution from as high as 1x1x1 mm^3 (small voxels) to as low as 7x7x7 mm^3 (large voxels).
- fMRI is a 4D SSTD (3D spatial dimensions and 1D time)
- Sona, Avesani et al, IJCNN, 2007; 2011

Pictures from: http://www.fmrib.ox.ac.uk

Neurogenetic STBD: The Allen Brain Institute Map (http://www.brain-map.org)



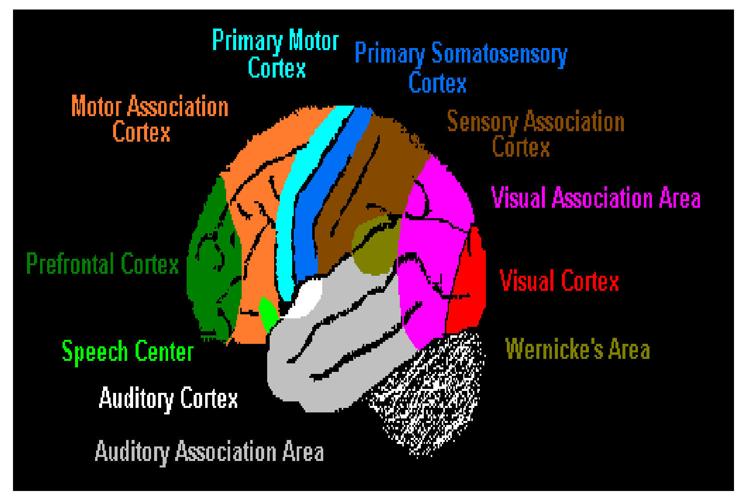


From the Brain Explorer: The Expression level of the genes (on the y-axis): ABAT A_23_P152505, ABAT A_24_P330684, ABAT CUST_52_PI416408490, ALDH5A1 A_24_P115007, ALDH5A1 A_24_P923353, ALDH5A1 A_24_P3761, AR A_23_P113111, AR CUST_16755_PI416261804, AR CUST_85_PI416408490, ARC A_23_P365738, ARC CUST_11672_PI416261804, 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)

2. The challenge is *MLM of STBD* and why standard ML techniques failed?

- Standard ML techniques: designed mainly for static data (e.g. MLP, SVM, regression; NB); training and recalled is vector by vector
- Time delayed NN: fixed number of time lags, but how many are optimal for the current time?
- Hidden Markov Models (HMM): require large training data for probability estimation;
- With the increased understanding of the brain processes, more brain-like *deep machine learning* methods are proposed: HMAX; Neocognitron (Fukushima). They are good for static data (e.g. images) rather than for STBD.
- Inspiration might come from understanding:
  - How does the brain learn?
  - How does it store 'time' and 'space'?

Challenge: How a system can learn from STBD about how the brain learns?



The Challenge – MLM of STBD

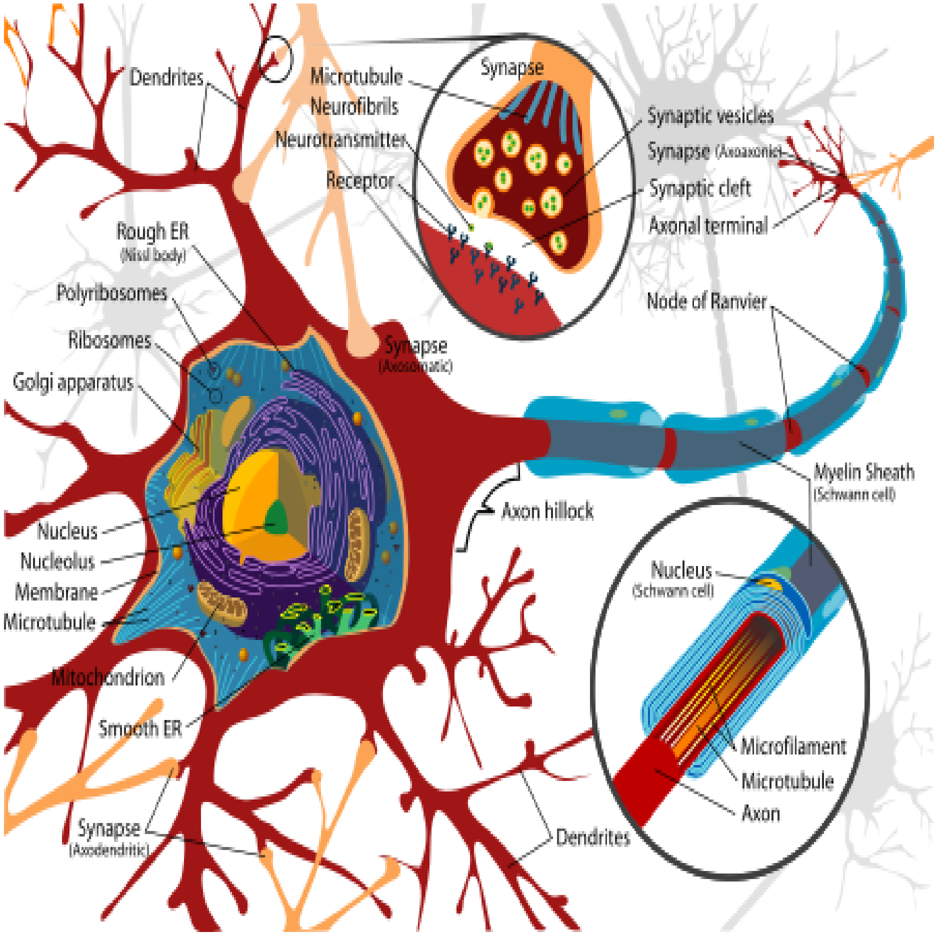
An enormous amount of data and prior knowledge about structural and functional characteristics of the human brain is available at present.

The challenge is how to use all this information and knowledge in order to create an *unifying* framework for STBD learning, mining and pattern recognition that would result in a better utilization of the vast amount of existing data, improved information processing accuracy and improved *understanding* of the brain data and the brain as the most complex information system – a result of hundreds of millions of years of evolution.

Open problems

1. Learning STBD utilizing both data and prior knowledge.
2. Interpretation of a model in order to reveal spatio-temporal relationships hidden in the STBD thus contributing to a better understanding.
3. Multimodal STBD learning, so that once a model is trained on one brain data set, it can be further trained on another data set of the same or other type related to the same subject (*personalised brain modelling*) or a population of subjects (statistical modelling).
4. Learning in one model both spatio-temporal *stimuli* data and related *response STBD* in their dynamic interaction.
5. Evaluating the efficiency of a model for STBD from information theoretic and information geometric view point (Amari).
6. Modeling and exploratory analysis of neurogenetic STBD.
7. Creating large associative memories from STBD
8. Predictive modeling of brain states from STBD.

2. Why spiking neural networks?



The mighty neuron!

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

Three, mutually interacting, memory types

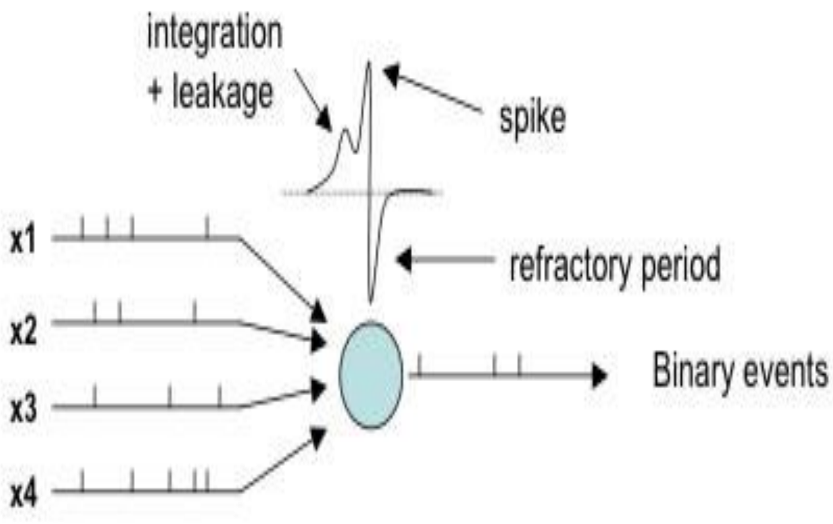
- short term;
- long term
- genetic

A neuron can accommodate spatial-, temporal-, and genetic information.

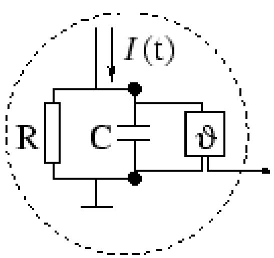
Challenge: SNN use the *same paradigm* of information processing as the brain, but how to utilise this for STBD?

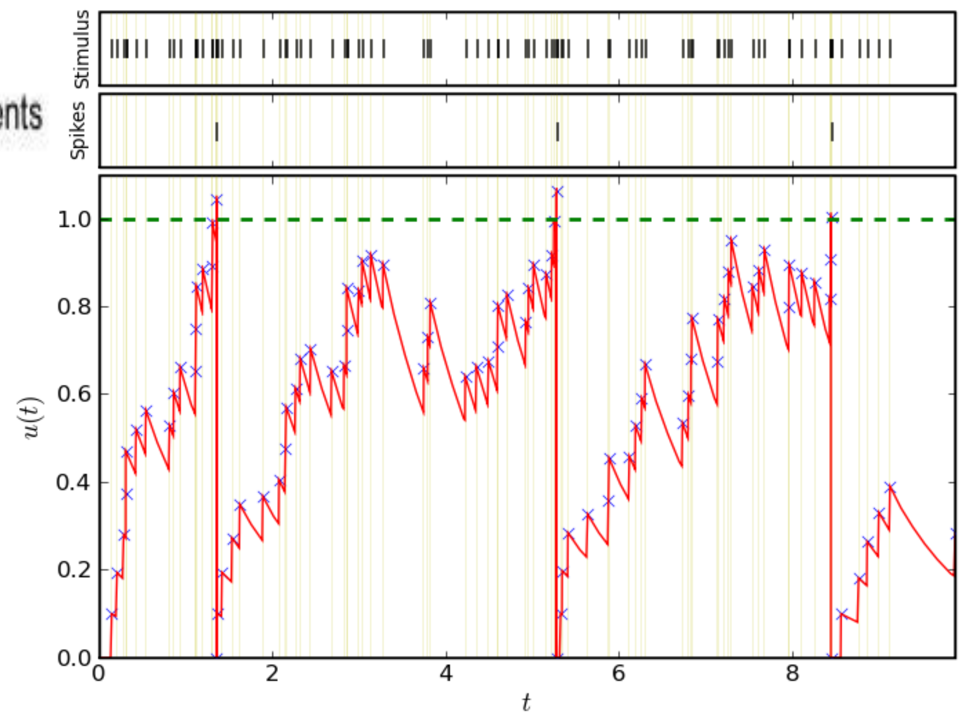
Models of spiking neurons:

(Hodgkin-Huxley 1952; Abbott, 2000; Maas, Izhikevich; other) .



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

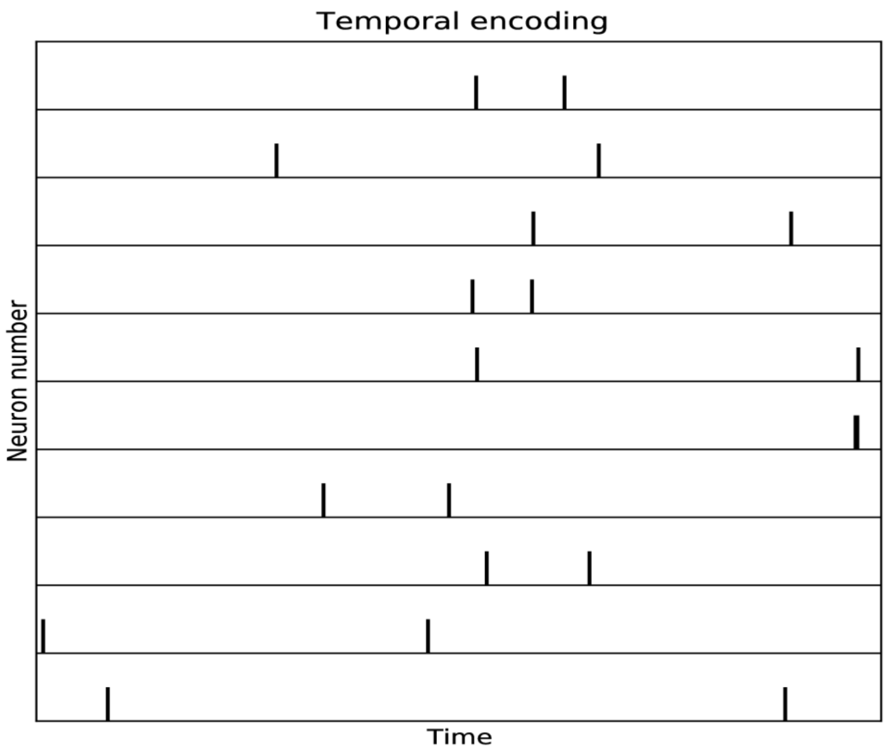




Rate - vs time-based coding of information as spikes

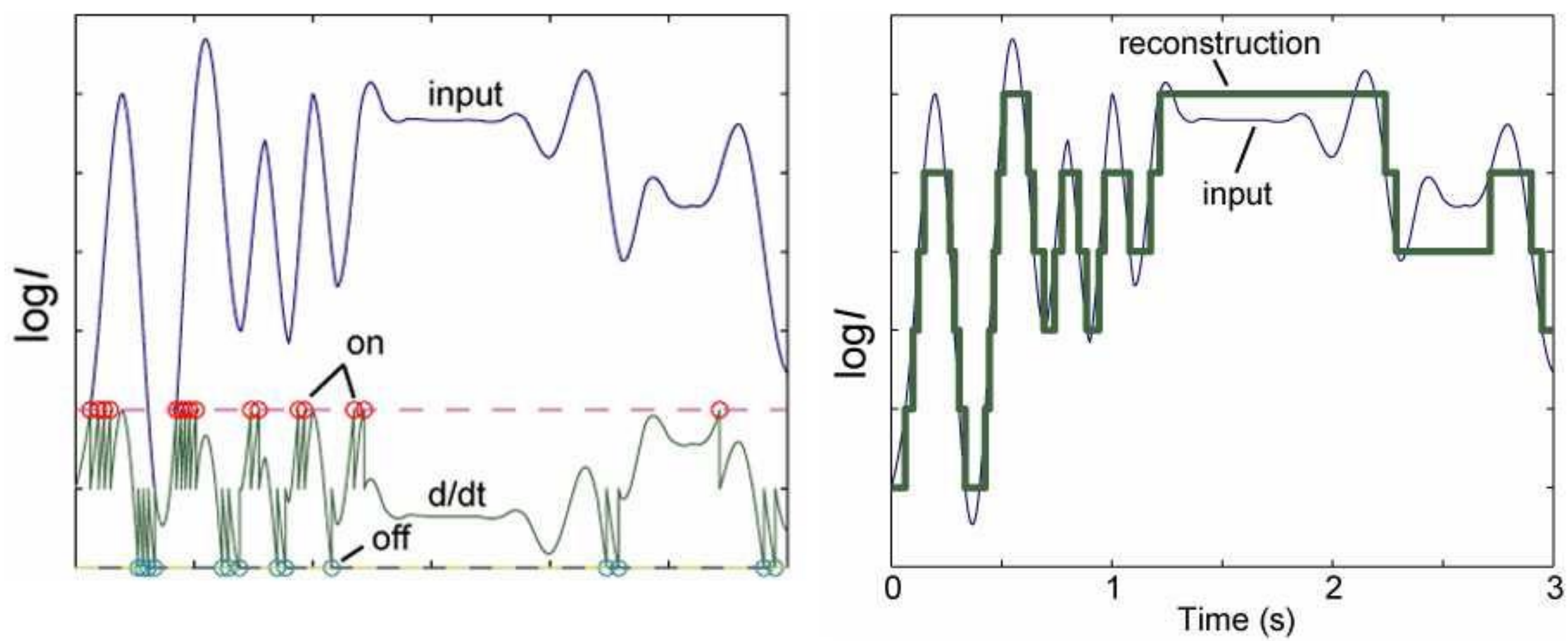
- Rate-based coding: A spiking characteristic within a time interval, e.g. frequency.

- Time-based (temporal) coding: Information is encoded in the time of spikes. Every spike matters!



Methods for transforming continuous input data into spikes

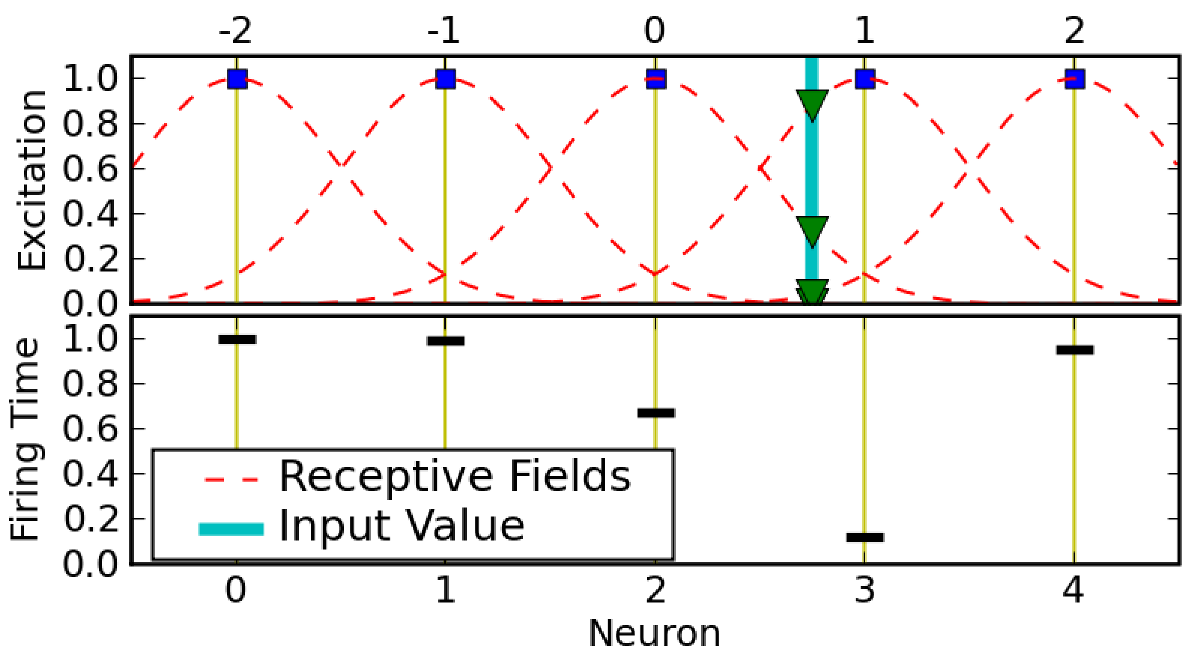
How does the brain do that?
Address event representation (AER)
Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128x128
Silicon Cochlea (Shih-Chii Liu, INI, ETH/UZH, Zurich)



Rank order population coding (RO-POC)

- A single real input value is distributed to multiple neurons and may cause the excitation and firing of several responding neurons at different times

- Implementation based on Gaussian receptive fields introduced by Bothe *et al*. 2002



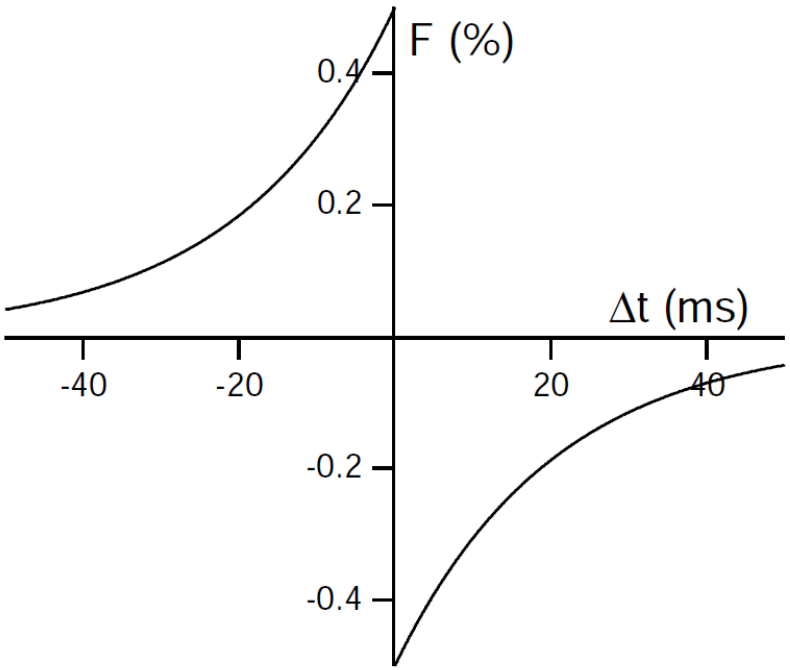
$$\mu = I_{\min} + (2*i-3)/2*(I_{\max} - I_{\min})/(M-2)$$

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.

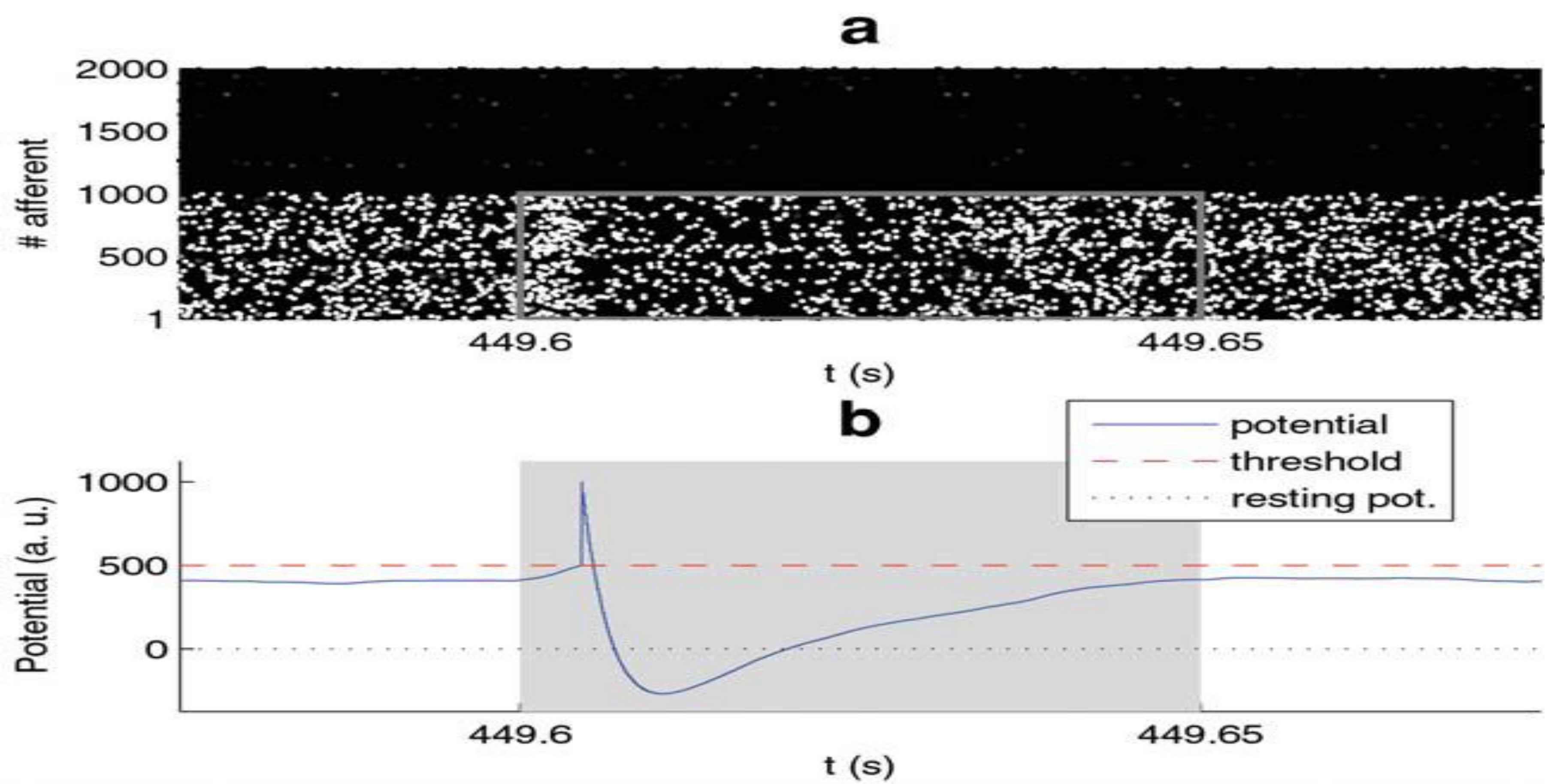
Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD

Δt=tpre -tpost



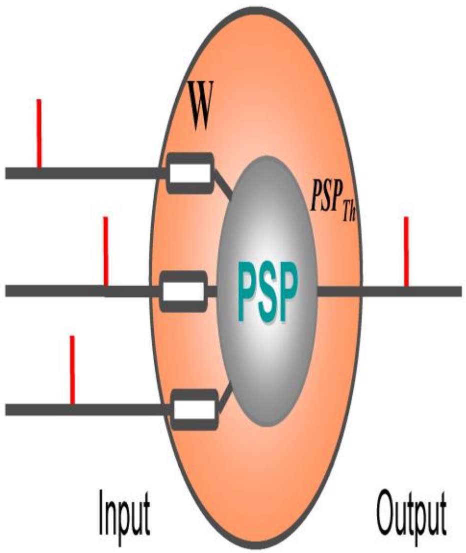
A single LIF with STDP can detect a spatio-temporal pattern

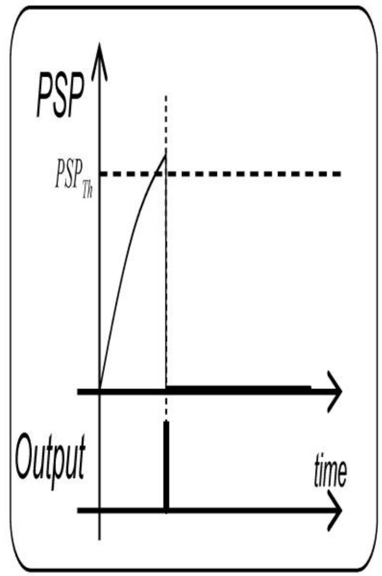
A single LIF neuron with simple synapses can be trained with the STDP unsupervised rule to discriminate a repeating pattern of synchronised spiking on several synapses from noise
(T. Masquelier, R. Guyonneau and S. Thorpe, PlosONE, Jan2008))



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

PSP_{Th}=C. PSPmax

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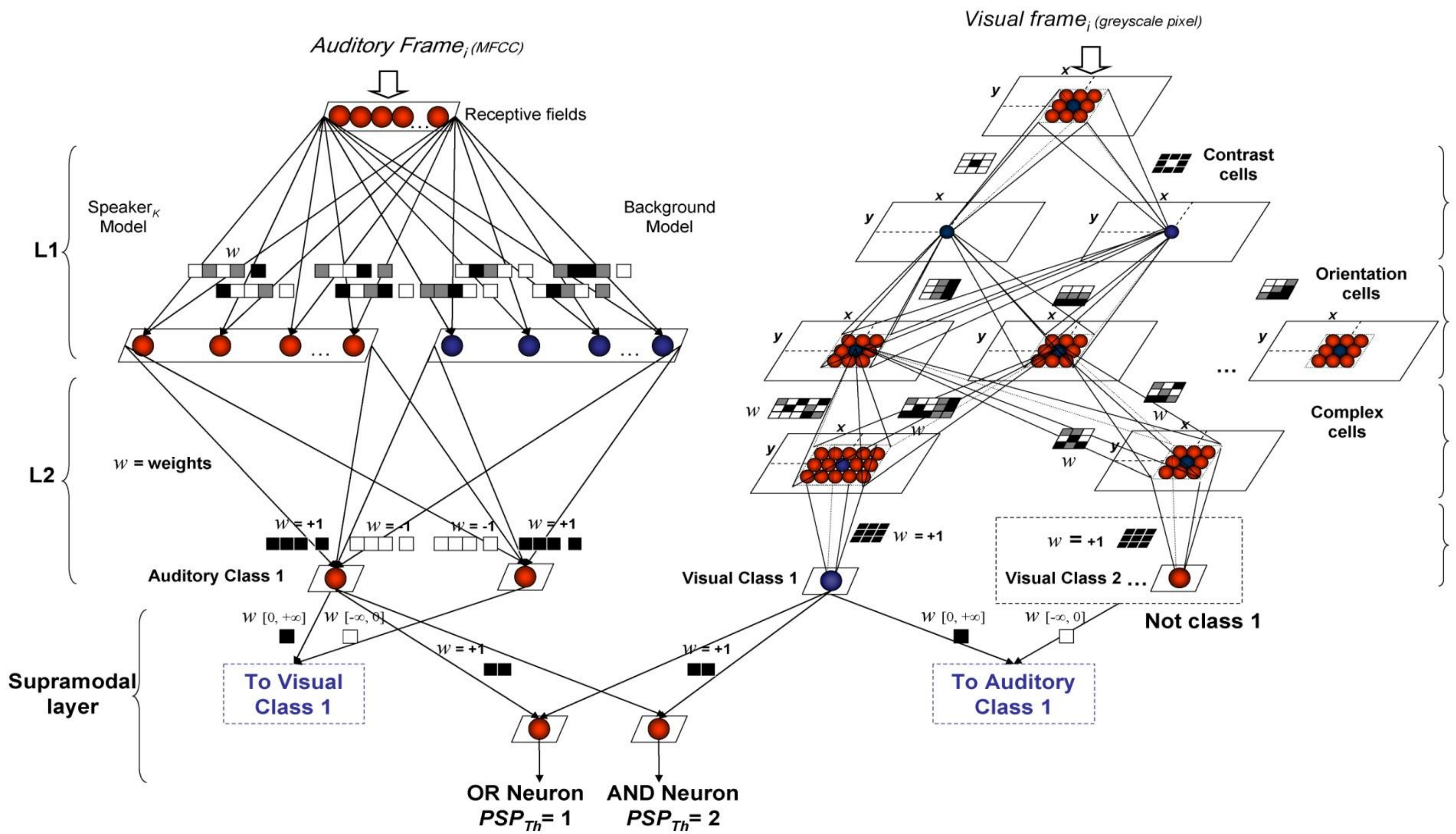
Building SNN: Evolving SNN (eSNN)
Example: Integrated audio-visual information processing

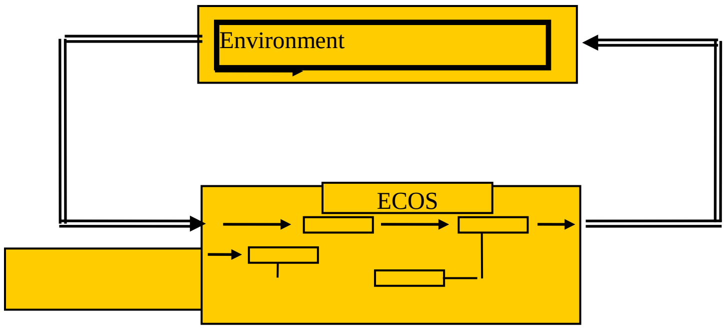
Person authentication based on speech and face data

(Wysoski, Benuskova and Kasabov, *Neural Networks*, 2010)



The Theory and the methods of Evolving Connectionist Systems (ECOS)

- ECOS are modular connectionist-based systems that evolve their structure and functionality in a continuous, self-organised, possibly on-line, adaptive, interactive way from incoming information, in a supervised and unsupervised way, facilitating knowledge discovery (Kasabov, 1998, 2002, 2007).

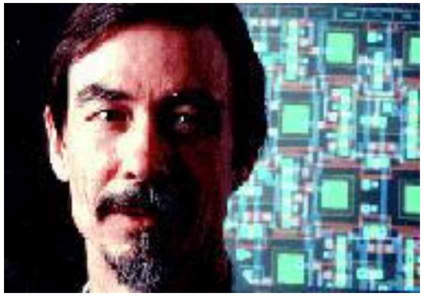


- Early ECOS models: RAN (J.Platt, 1991) – evolving RBF NN; Incremental FuzzyARTMAP (Carpenter , Grossberg); Growing gas; EFuNN (Kasabov, 1998, 2001); ESOM (Deng and Kasabov, 2002); DENFIS (Kasabov, Song, 2002); EFuRS, eTS (Angelov, 2002;Filev, 2002).

- M.Watts, *Ten years of Kasabov's evolving connectionist systems, IEEE Tr SMC- part B, 2008.*

- New developments: Ensembles of EFuNNs (T. Ljudemir, 2008-); Application oriented ECOS (B.Gabric, R.Duro, McGinitty et al.); Incremental feature selection (Ozawa, Kasabov, Polikar, Minhu Lee, Pang), eSNN, QieSNN, other.

Technological progress in neuromorphic computation



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);

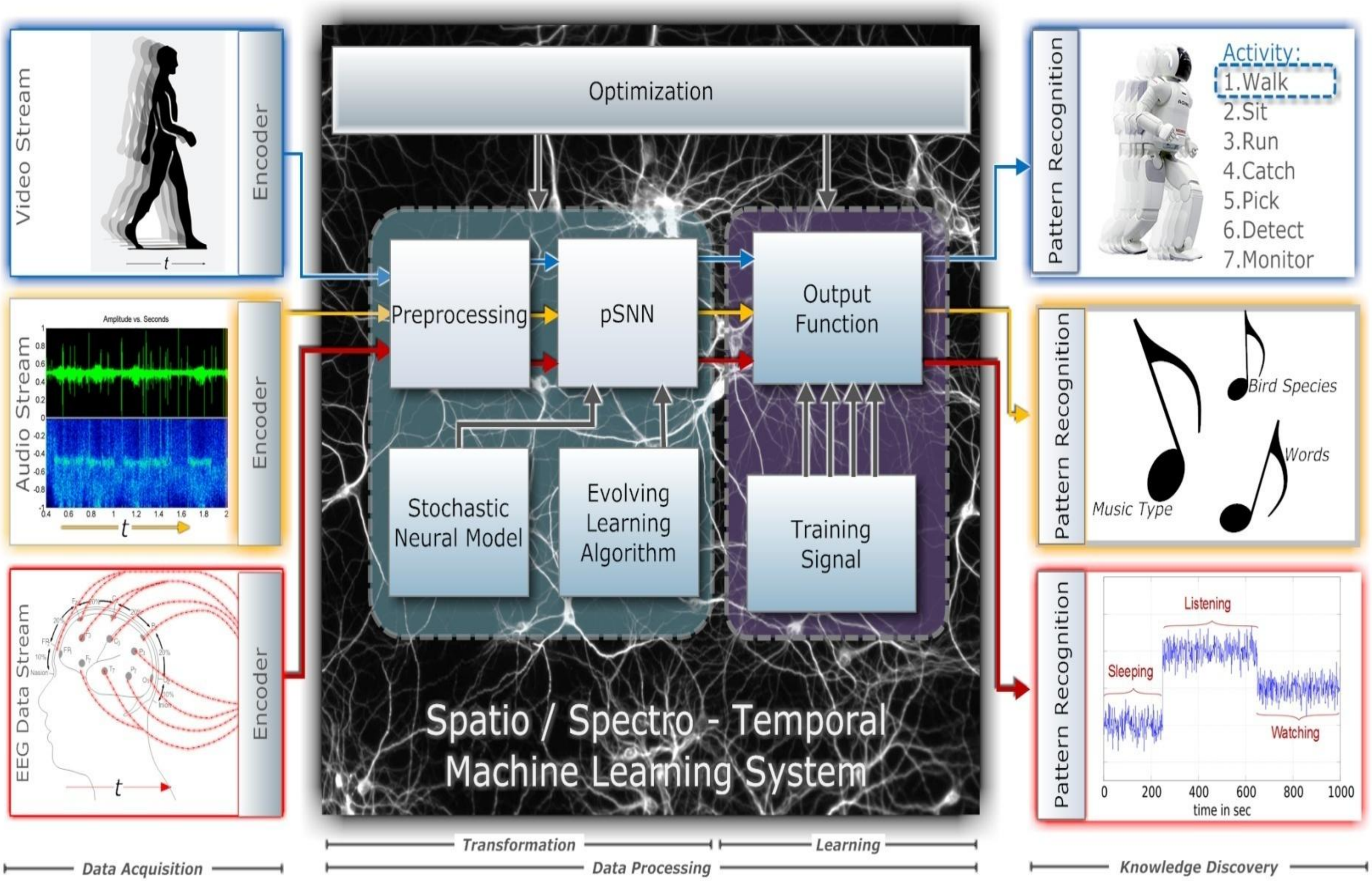
The IBM chip (D.Modha, 2012): 256 LIF neurons and 64k synapses in a chip.

U. Manchester SpiNNaker (2^{16} computer chips, 2011; 1 mln neurons 2013)

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

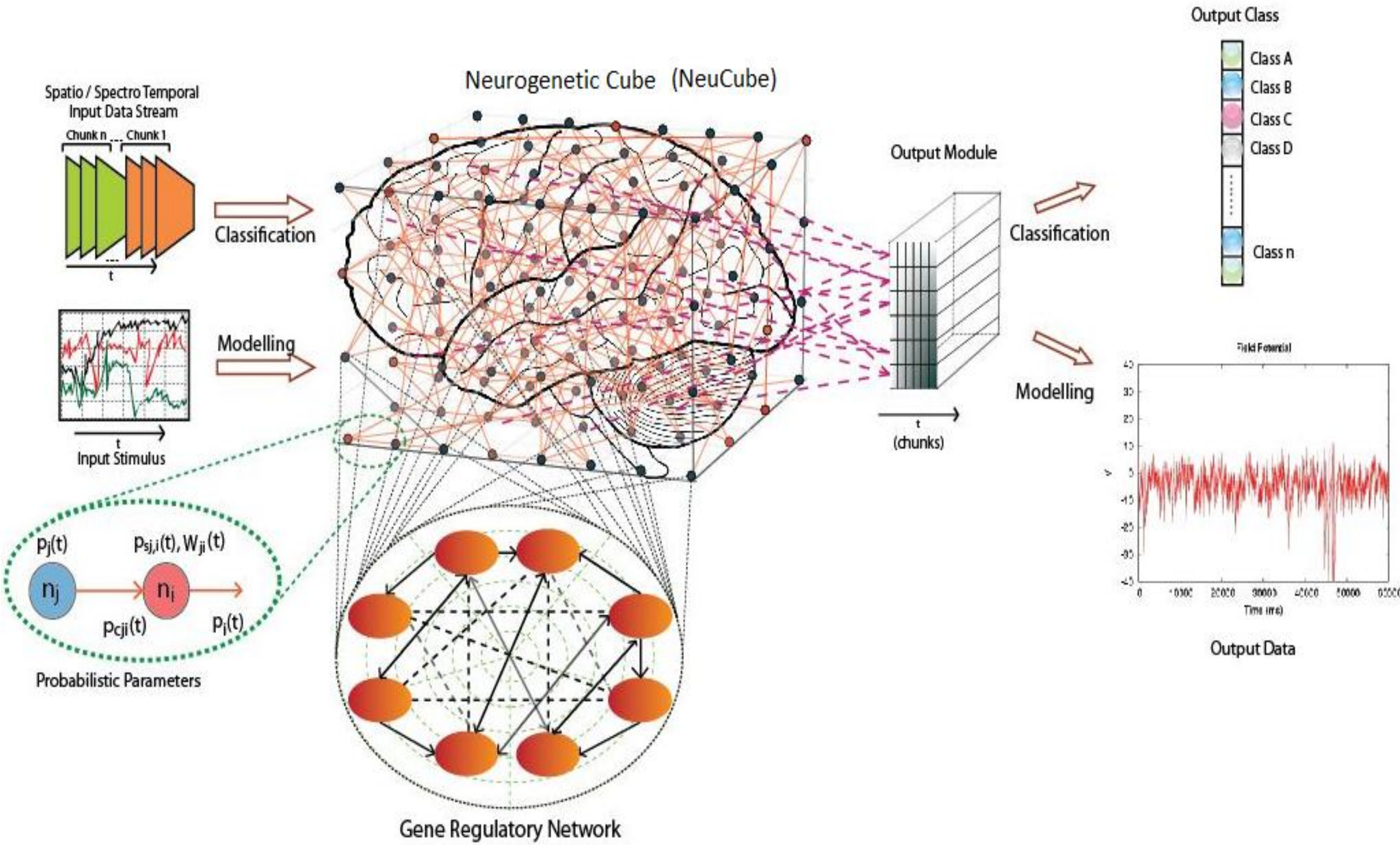
The challenge: SNN technology is available, but how do we use it for STBD?

4. The EvoSpike project (ncs.ethz.ch/projects/evospike) and the *NeuCube* Framework



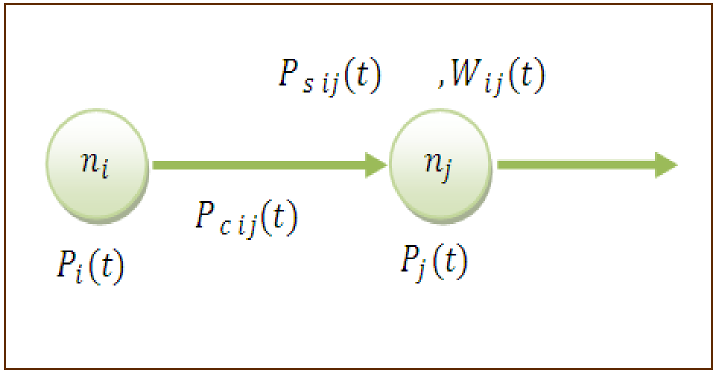
A spiking **Neu**rogenetic **Cube** (NeuCube) Framework

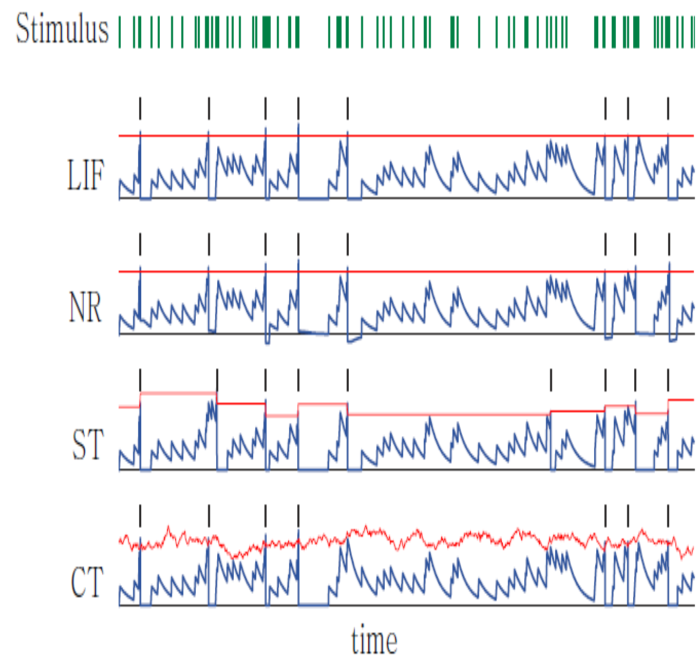
(Kasabov, LNAI 7477, 2012)



(a) A probabilistic neurogenetic spiking neuron model (PNGM)

(Kasabov, Neural Networks, Jan. 2010; Kasabov et al, 2005))





The information is represented as connection weights, probabilistic and gene 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 PNGM is reduced to LIF model.

Gene parameters of the PNGM

Four types of synapses, (Kasabov, Benuskova, Wysoski, 2005)

Table. Neuronal Parameters and Related Proteins

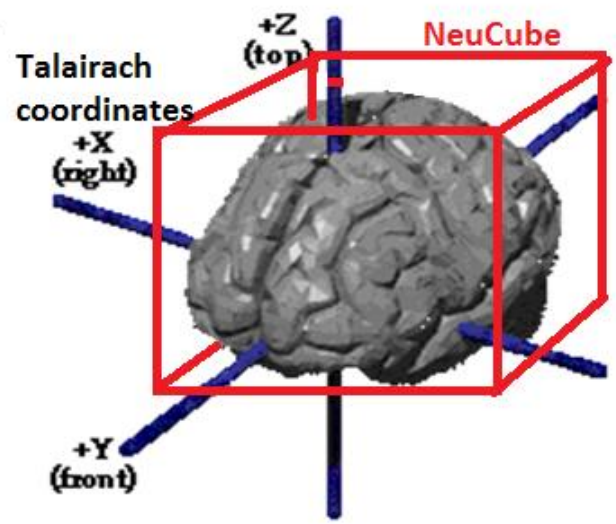
Neuronal parameter Amplitude and time constants of	Protein
Fast excitation PSP	AMPAR
Slow excitation PSP	NMDAR
Fast inhibition PSP	GABRA
Slow inhibition PSP	GABRB
Firing threshold	SCN, KCN, CLC
Late excitatory PSP through GABRA	PV

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

type = fast excitation, slow_excitation, fast_inhibition, slow_inhibition

(b) Mapping the *structure* of STBD Data into NeuCube

- Mapping directly data points (e.g.: voxels, EEG channels, electrode positions) into neurons
- Clustering data points before mapping (e.g. clusters of 2^3 voxels)
- Mapping multiple subject and multiple type data requires unified mapping scheme
- Using the MNI coordinates will require 139 x 188 x 146= 3,815,272 neurons at minimum for 1mm resolution and only 4,000 neurons for 1cm resolution
- Using Talairach Atlas, 1988 - (ww.talairach.org/daemon.html) ;
- Mapping EEG, fMRI, gene data points to standard MNI and/or Talairach coordinates



(c) Learning STBD in a NeuCube Architecture

- Initialisation of the connections in the NeuCube following brain strucures

- Unsupervised learning:

SSTD is entered into relevant areas of the Cube over time and unsupervised learning is used to adapt the connection weights. The NeuCube will learn to activate similar spiking trajectories when similar input stimuli are presented – a *polychronisation* effect (Izhikevich).

- Supervised learning:

Same SSTD used for training is now propagated again through the trained NeuCube and output neurons are trained to classify the state of the cube into pre-defined labels (or output spike sequences). As a special case, all neurons from the NeuCube are connected to every output neuron. Feedback connections from output neurons to neurons in the NeuCube can be created for reinforcement learning.

NeuCube as Spatio-Temporal Memory
Finite Automata with Spatio-Temporal states (FAST)

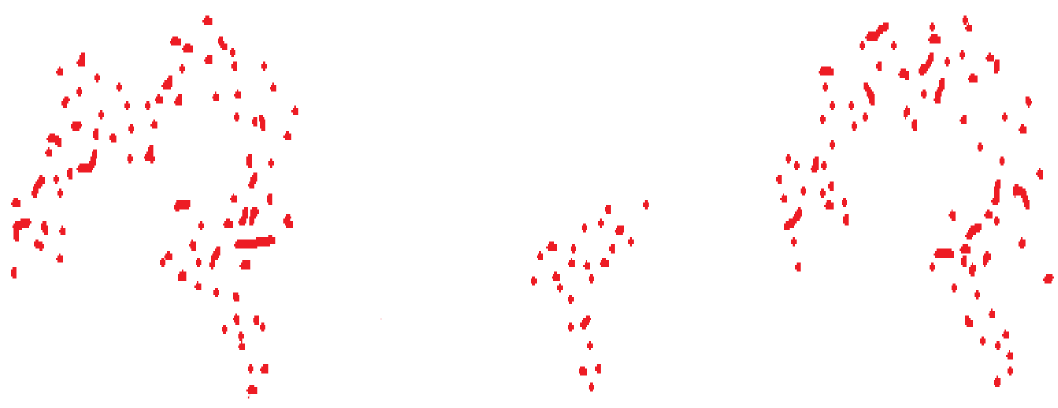
The NeuCube memory is represented as:

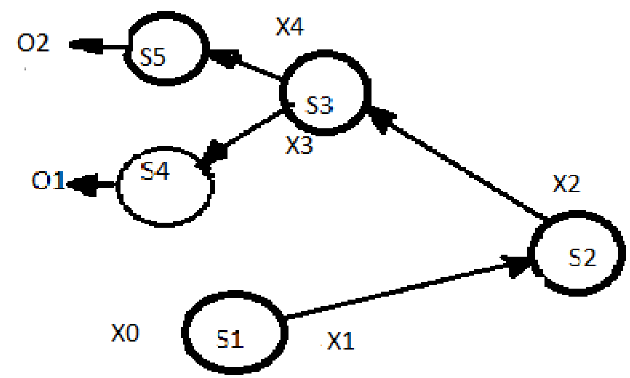
(a) Short-term memory, represented as changes of the PSP and temporary changes of synaptic efficacy;

(b) Long-term memory, represented as a stable establishment of synaptic efficacy;

(c) Genetic memory, represented as a change in the gene/ protein expression levels as a result of the above short-term and long term memory changes and evolutionary processes

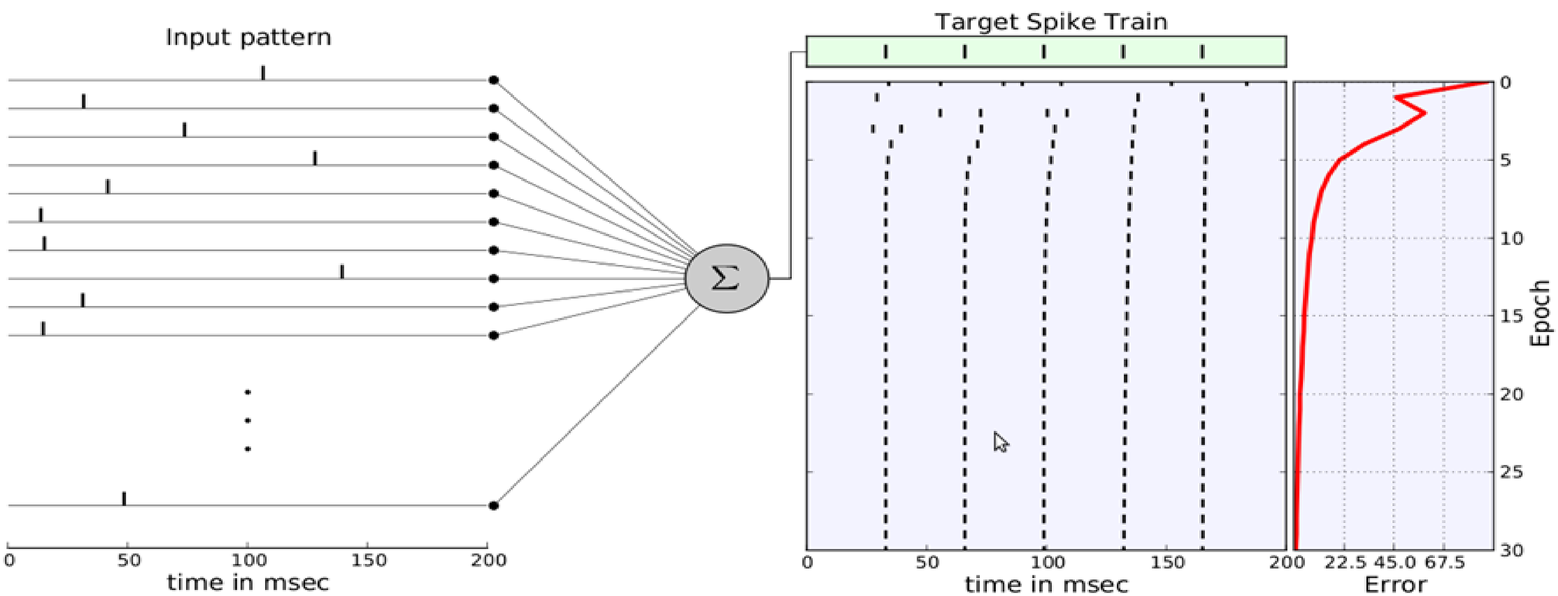
(d) Spatio-temporal memory – a global associative memory, or FA, of spatio-temporal states





(d) Output classifiers for the NeuCube states
SPAN: Spike Pattern Association Neuron

(A.Mohhemed et al, EANN 2011, IJCNN 2012, ICONIP2011 and 2012, IJNS 2012; Neurocomputing 2012)

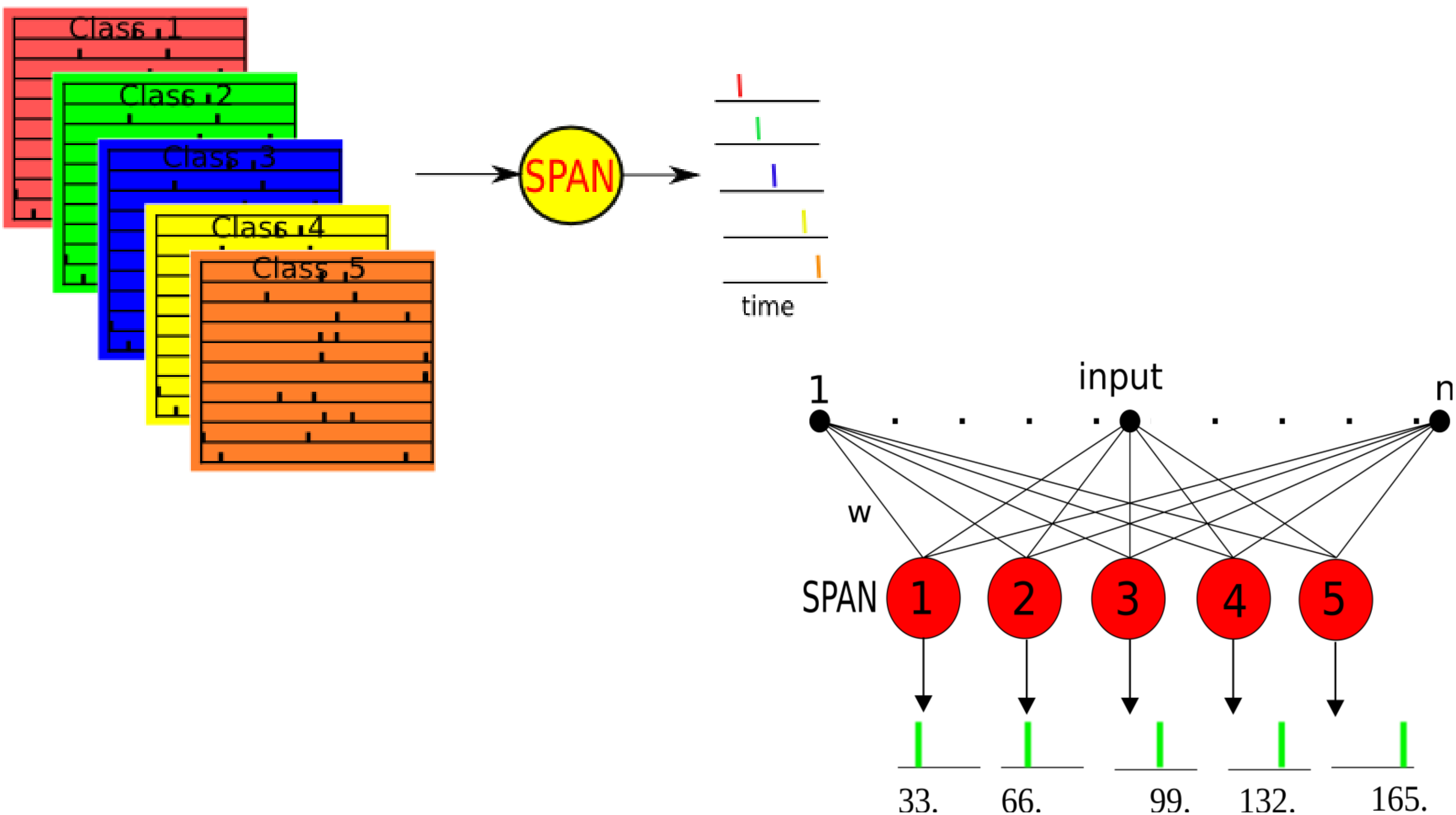


A single output neuron is trained to respond with a temporally precise output spike train to a specific spatio-temporal input.

Other spike pattern association neuronal models: SpikeProp; ReSuMe; Tempotron; Chronotron.

Evolving multiple SPAN classifiers and spike pattern generators

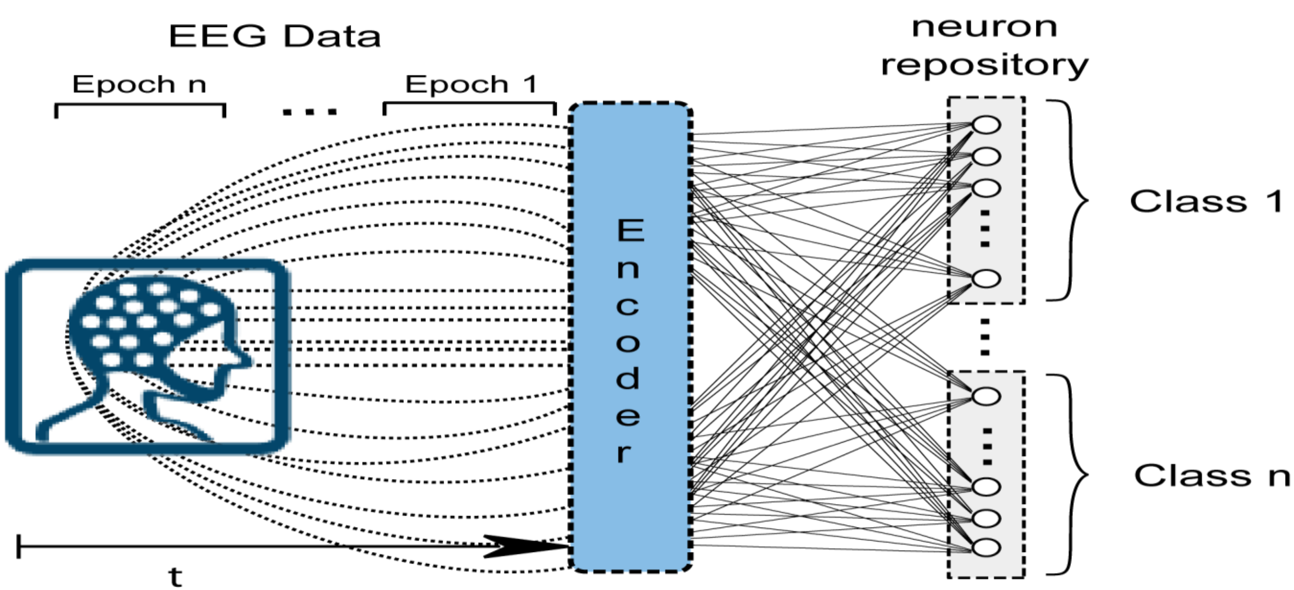
(Batch mode and incremental learning algorithms)



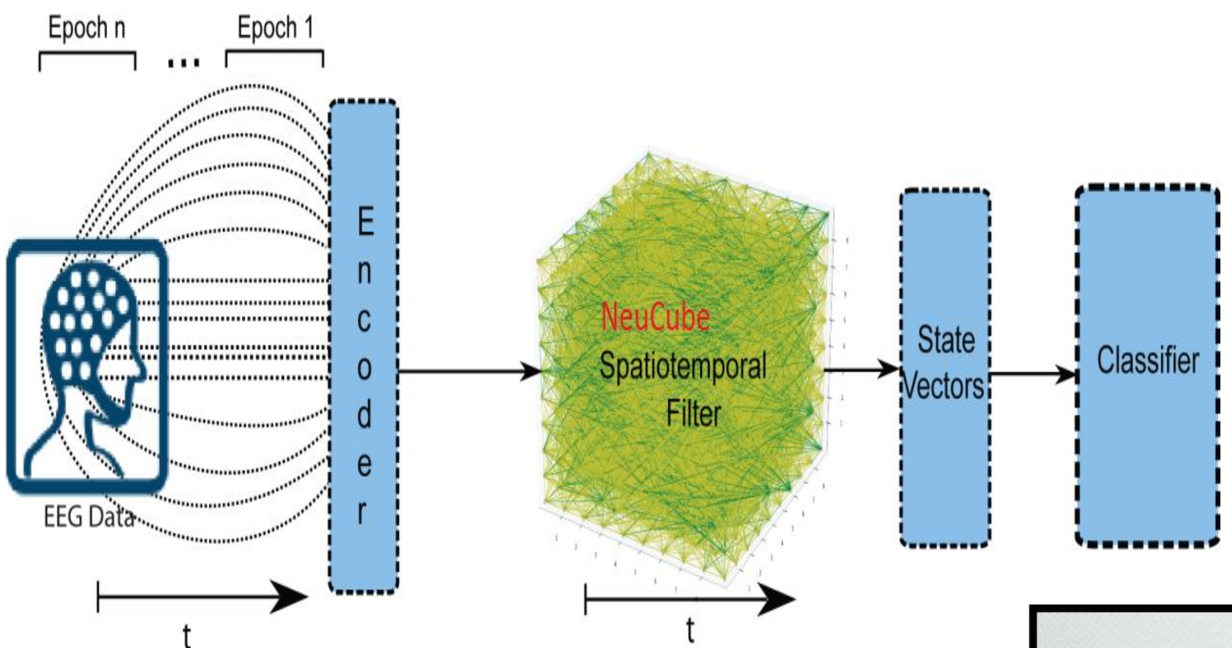
Dynamic Evolving SNN (deSNN) classifier

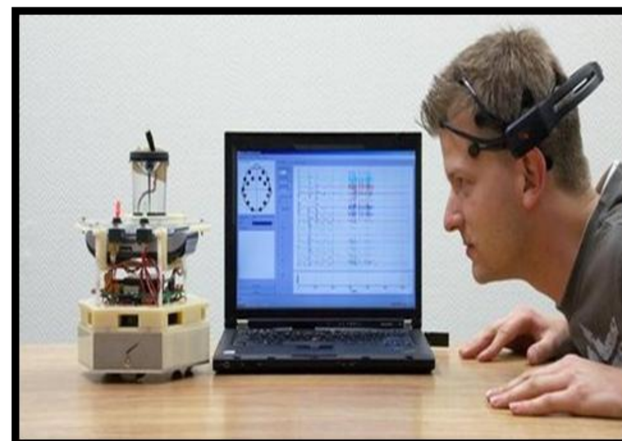
(Kasabov, Dhoble, Nuntalid, Indivery, WCCI 2012, Neural Networks 2012)

- Combine RO learning for weight initialisation based on the first spikes and SDSP 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.
- Example of using deSNN for EEG STBD classification:

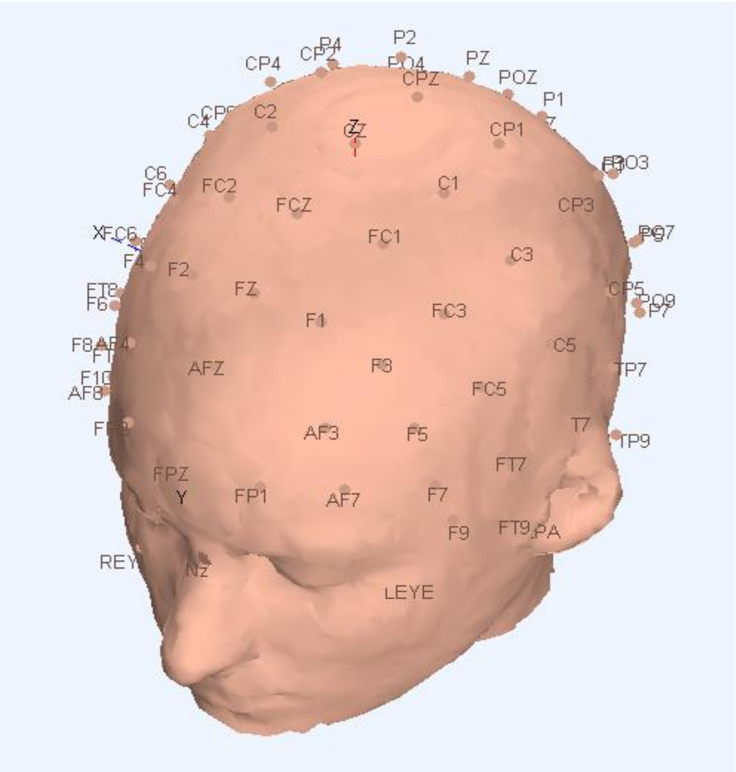


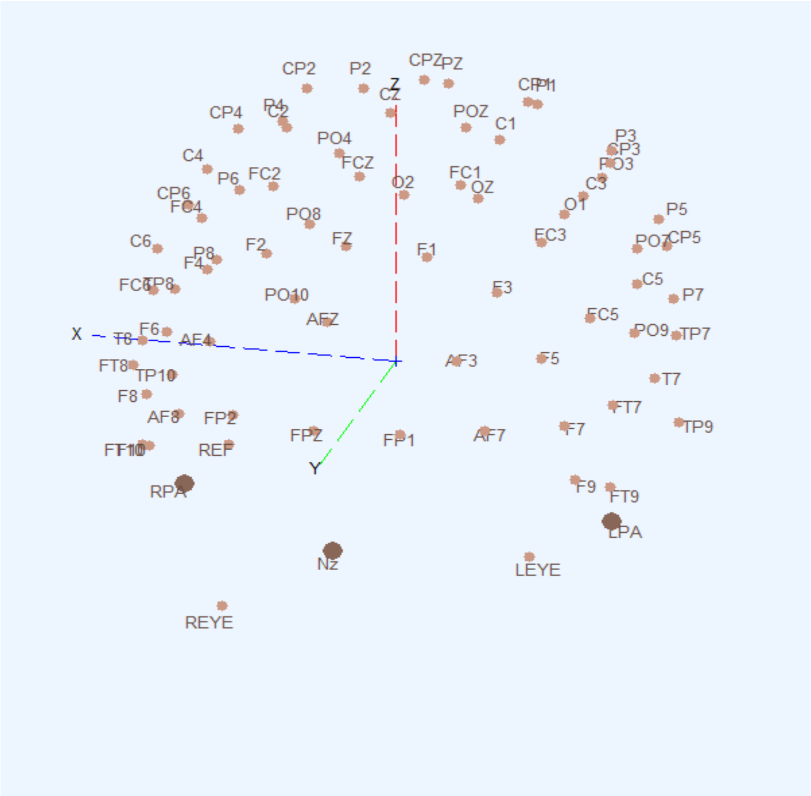
5. NeuCube for EEG and fMRI STBD





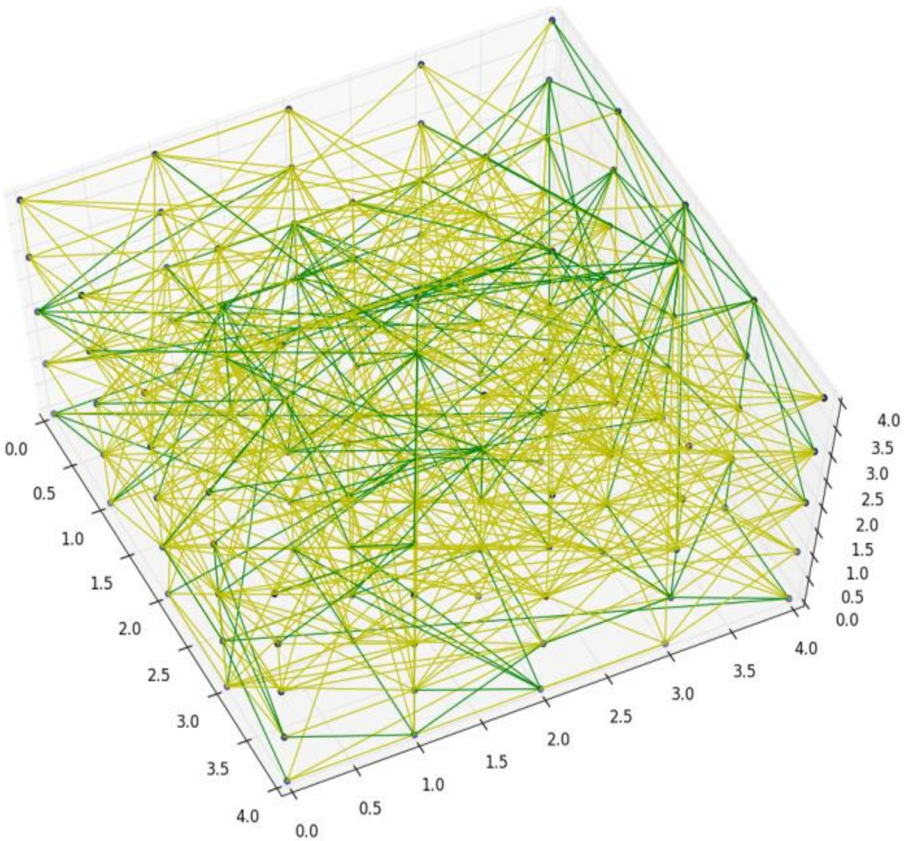
Spatial Mapping of EEG channels into 3D NeuCube space

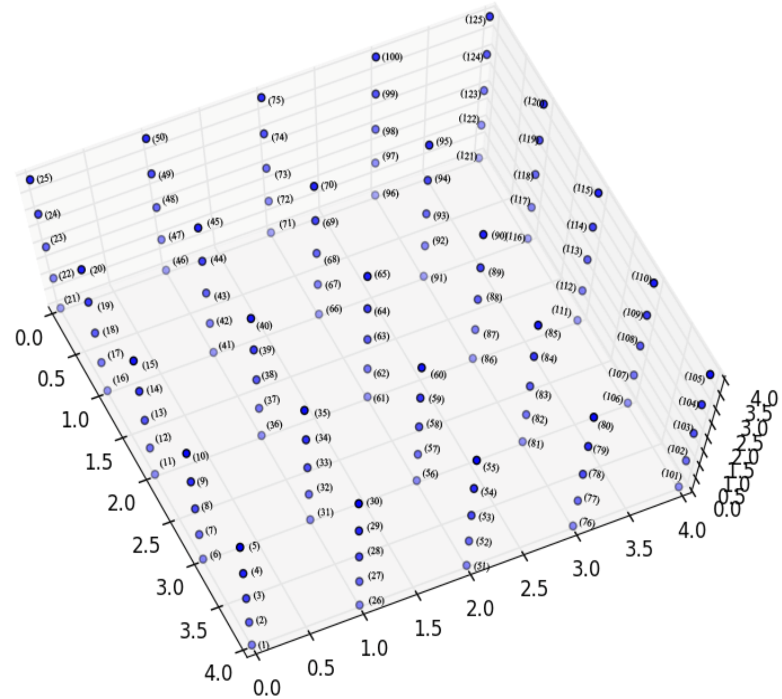




nkasabov@aut.ac.nz

Example of a simple architecture for mapping 64 EEG channels into 5x5x5=125 NeuCube neurons

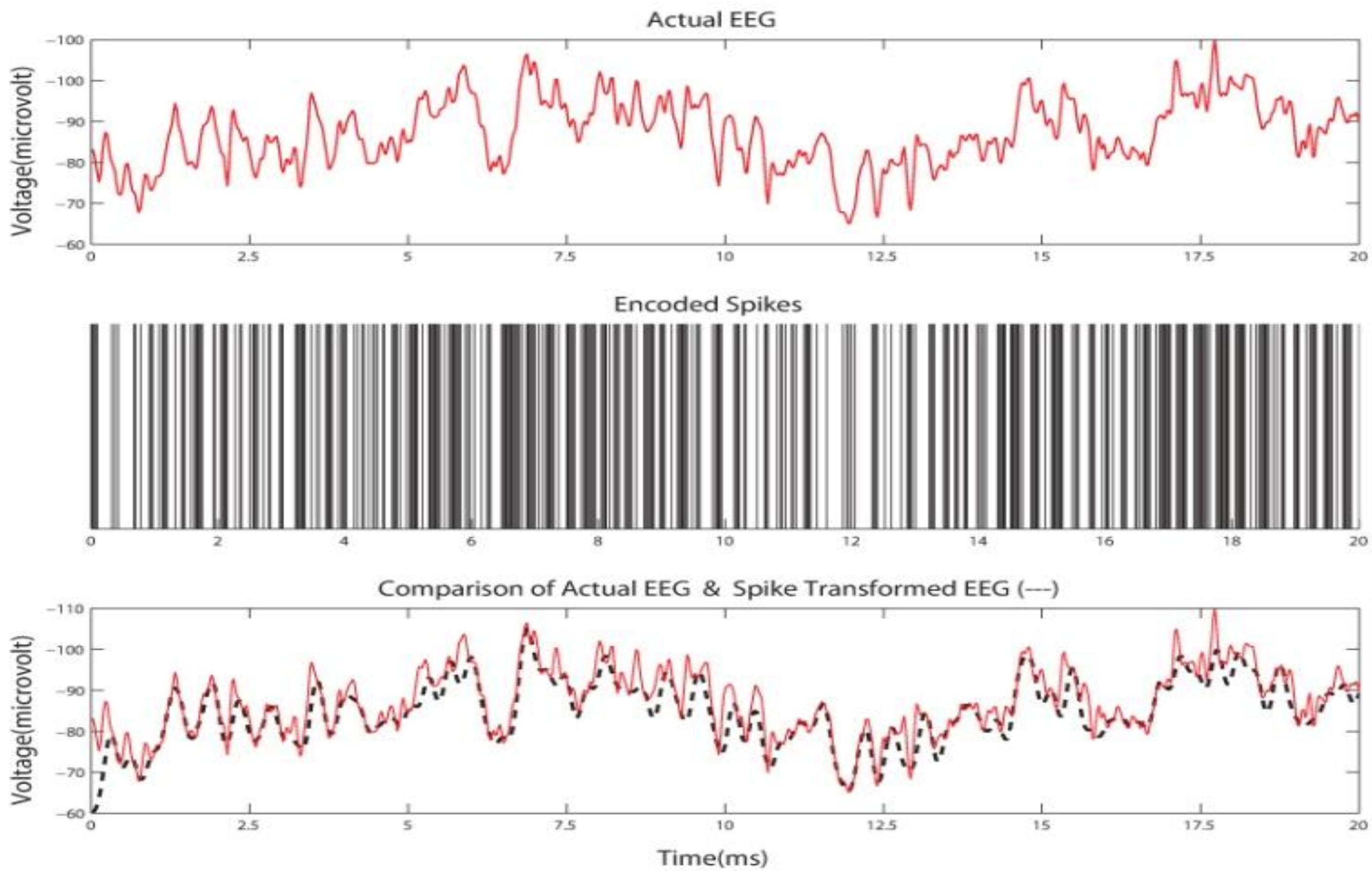




Encoding EEG signals into spikes using the BSA (Ben's Spike Algorithm)

(N.Nuntalid and N.Kasabov, ICONIP2011; Nuntalid et al, Evolving Systems, 2012)

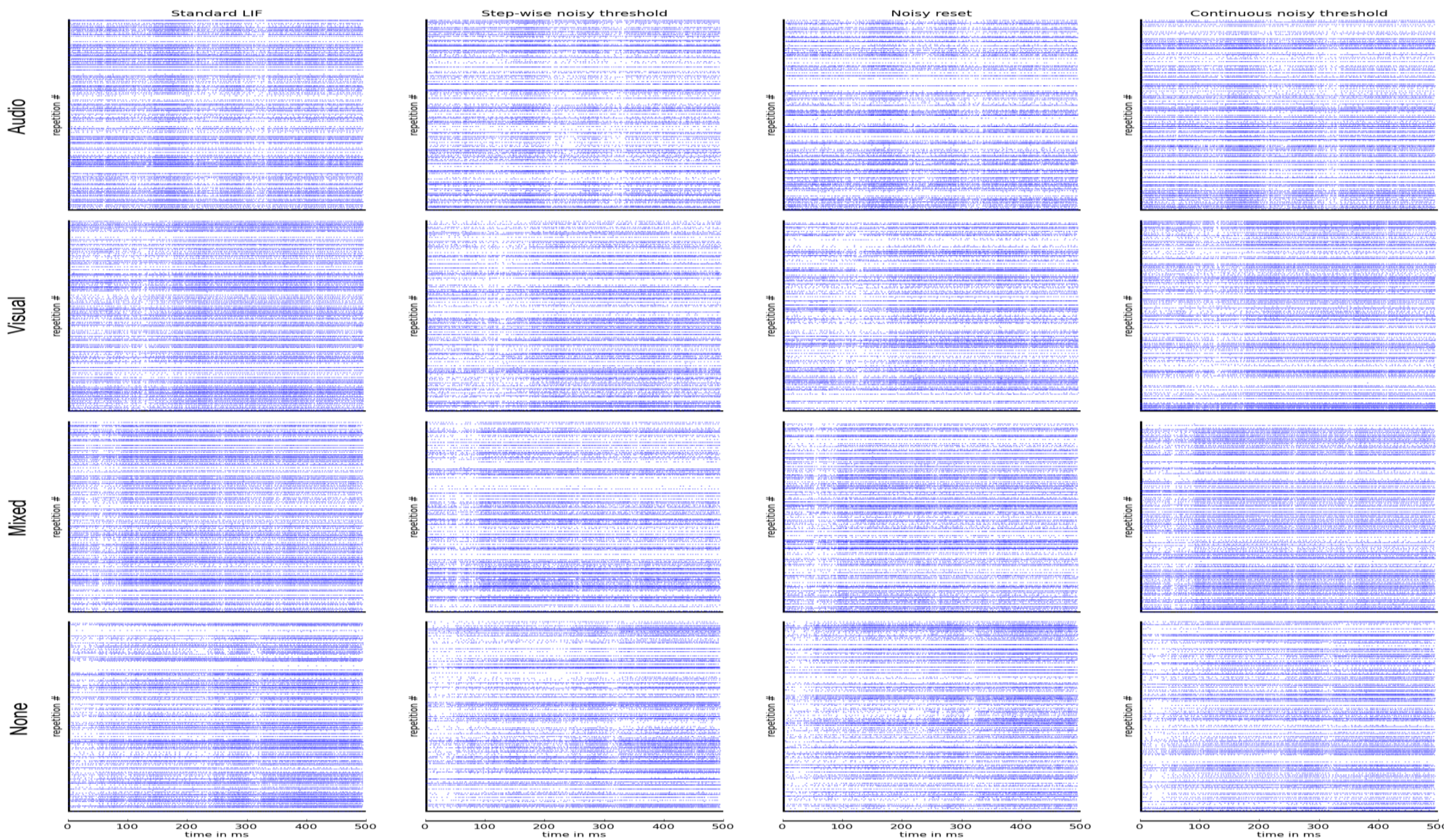
BSA: (Schrauwen and van Campenhout, 2003)



A case study problem: Learning EEG STBD

Brain response to four stimuli: image; sound; both; none.

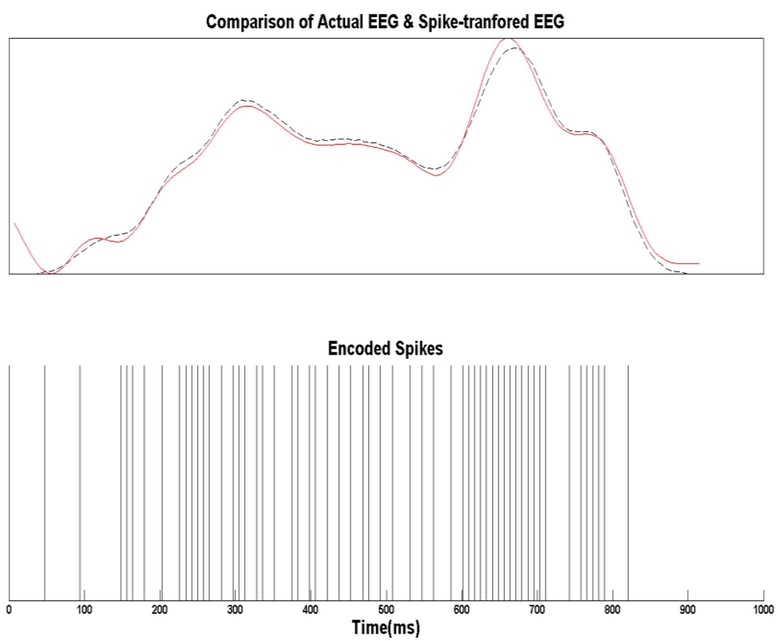
Data collected in RIKEN by C. van Leuwen (2000)



Case study: P300 STBD

Data from EPFL BCI group, http://bci.epfl.ch/p300; 32 channel EEG

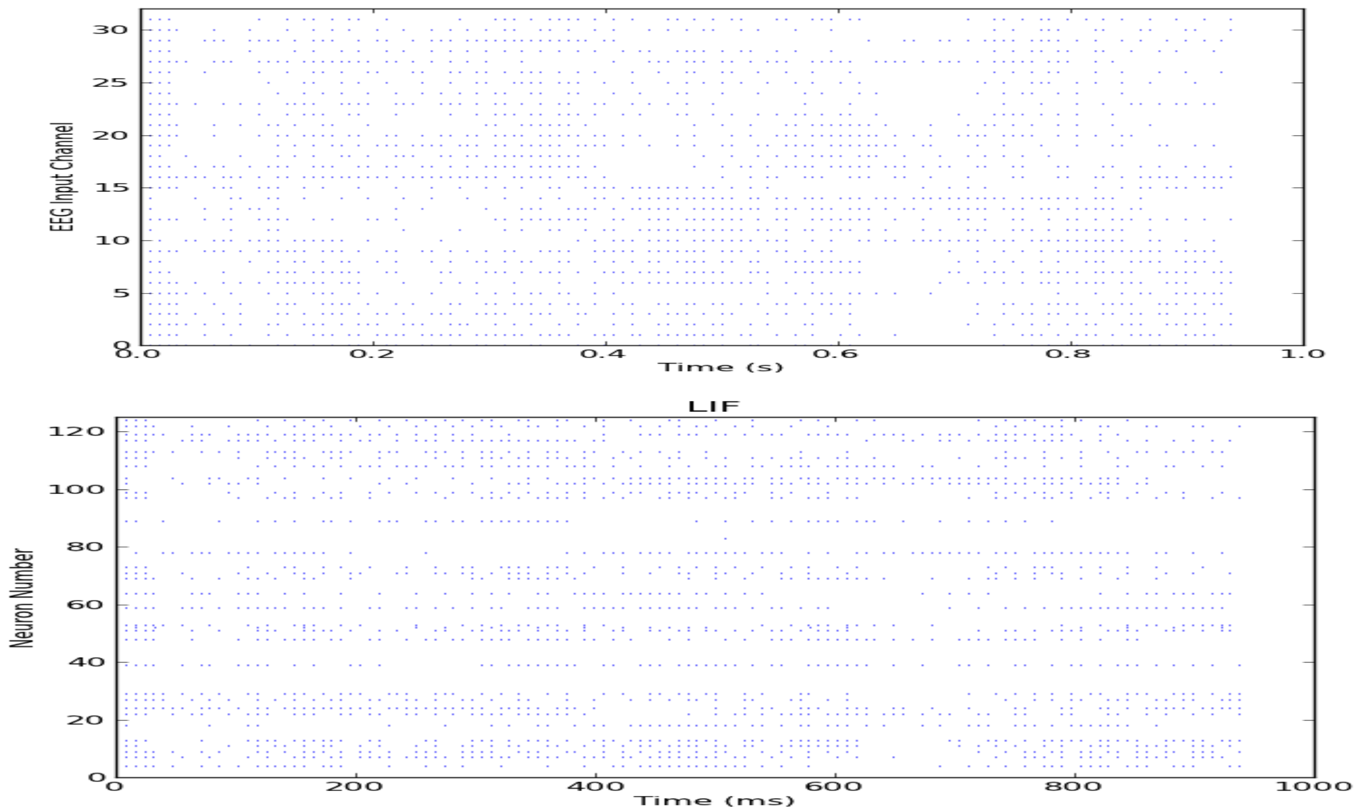
Transforming EEG STBD into spike trains



Mapping 32 EEG channels into 5x5x5=125 NeuCube neurons

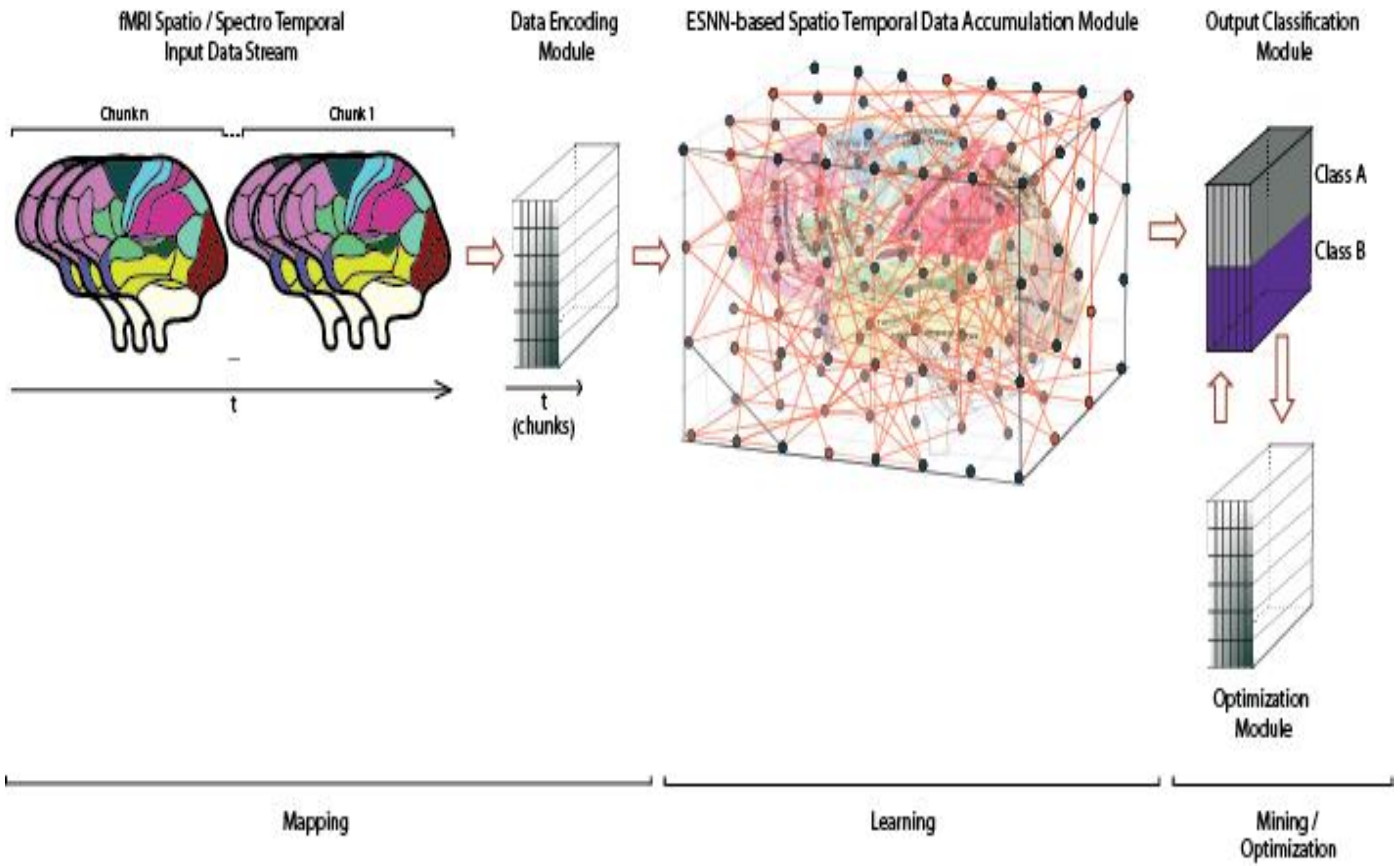
EEG	NeuCube	EEG	NeuCube
Fz	5	F7	52
Cz	65	F3	54
Pz	125	F4	14
Oz	123	F8	12
T7	103	P7	112
C3	105	P3	114
C4	25	P4	74
T8	23	P8	72
FC5	79	AF3	30
FC1	60	AF4	10
FC2	40	PO3	120
FC6	19	PO4	100
CP5	109	FP1	28
CP1	90	FP2	8
CP2	70	O1	118
CP6	49	O2	98

P300 BCI with NeuCube (98.92% accuracy)



Methods	Accuracy	Number of iterations for training
Gradient Boosting	86%	150
deSNN	85%	1
NeuCube	98.92%	1
		(no training of the Cube, deSNN as classifier)

NeuCube for fMRI STBD

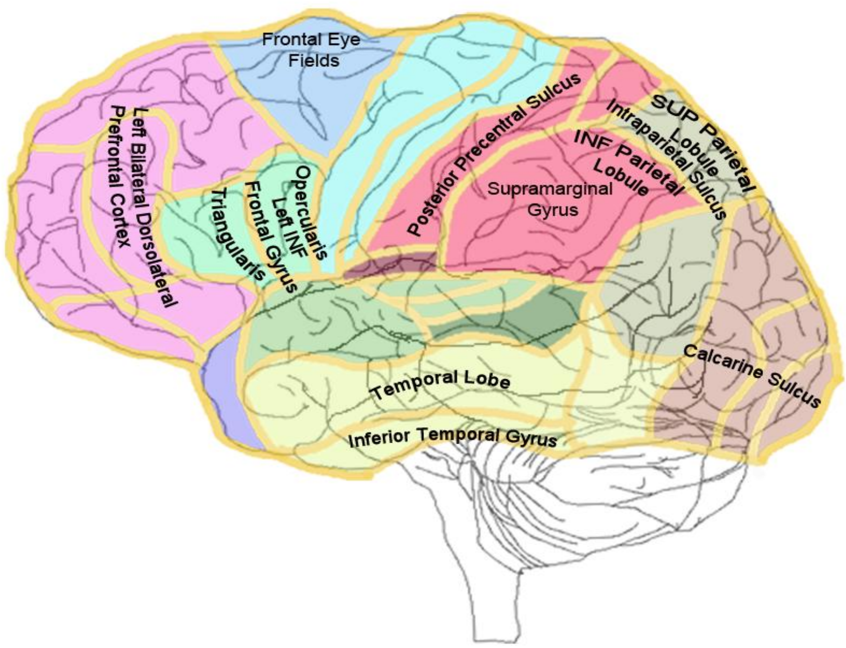


Case study example: The StarPlus Data

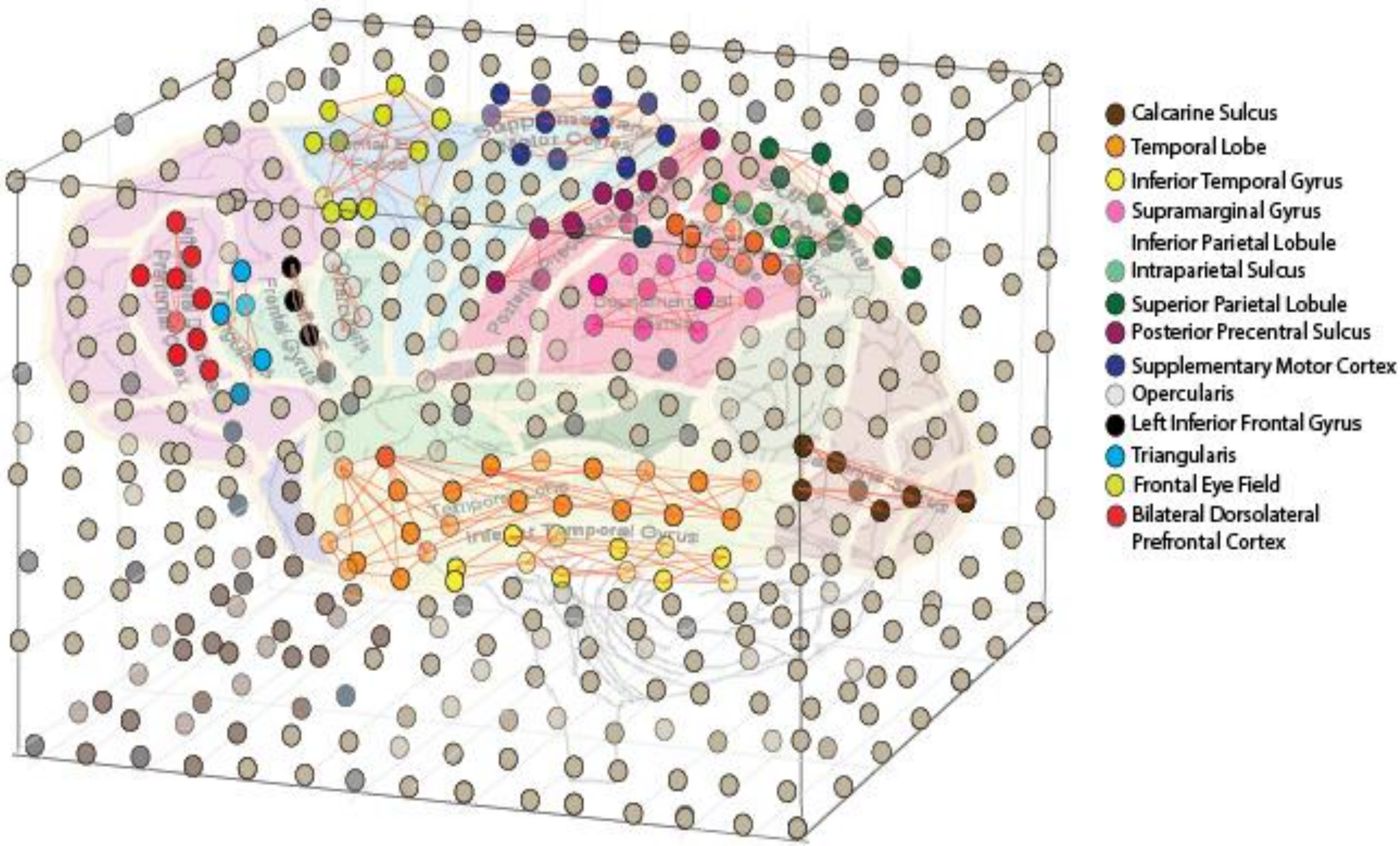
(http://www.cs.cmu.edu/afs/cs.cmu.edu/project/theo-81/www/)
Mitchell et al (2004) and http://www.cs.cmu.edu/afs/cs.cmu.edu/project/theo-81/www/.

The data: 13 subjects shown pictures and sentences
Problems: 1. Classification of cognitive states – 'picture' vs 'sentence'
2. Classification of state of reading ambiguous vs non-ambiguous sentence

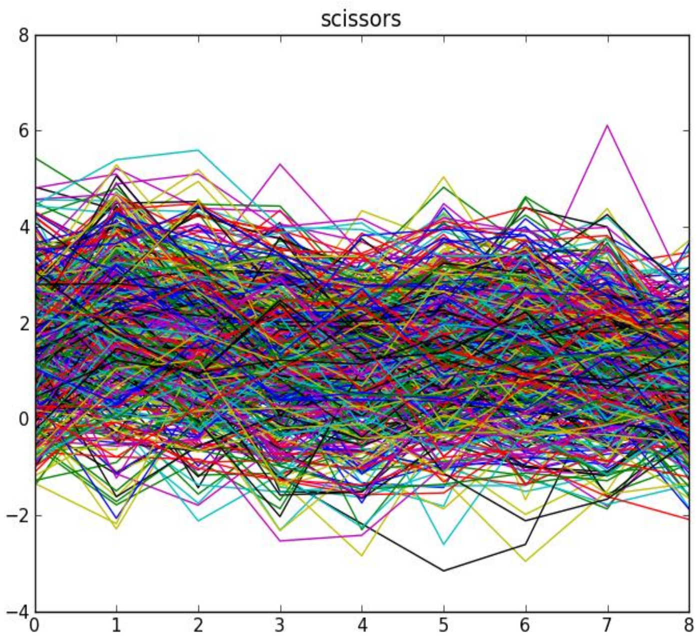
Results: Appr. 10% error for a single subject and 20% for multiple subjects using SVM.
Problems: Data is not treated as STBD, but by ROI only (see figs)

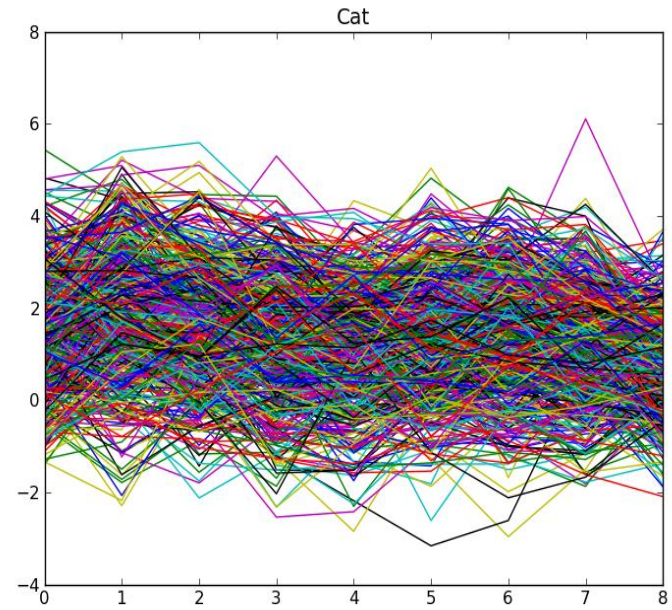


Mapping StarPlus data into NeuCube



Transforming fMRI voxel data into spike trains





Dynamical change of voxel values of fMRI scan over 9 time units when a subject is viewing different objects – *scissors* and a *cat* (from http://www.pymvpa.org/)

6. Computational Neuro-Genetic Modelling of STBD

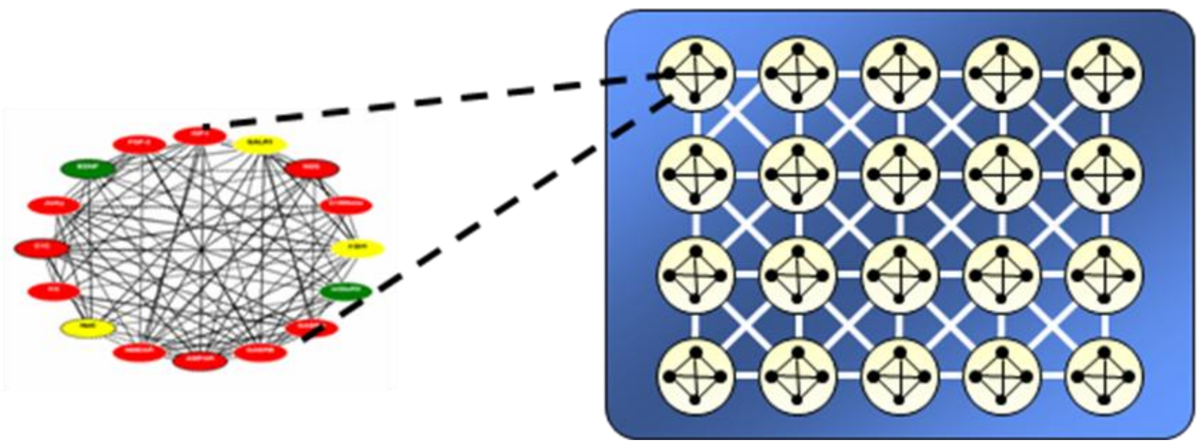
Challenge: How to add dynamic gene data to a SNN structure?

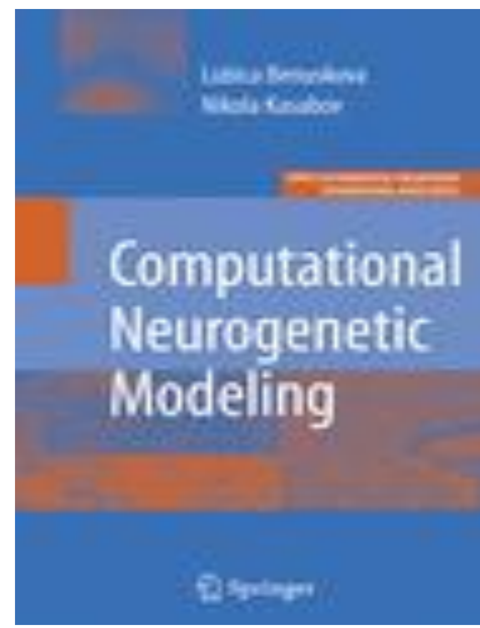
- CNGM incorporate gene regulatory networks (GRN) in a SNN structure.

- 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.

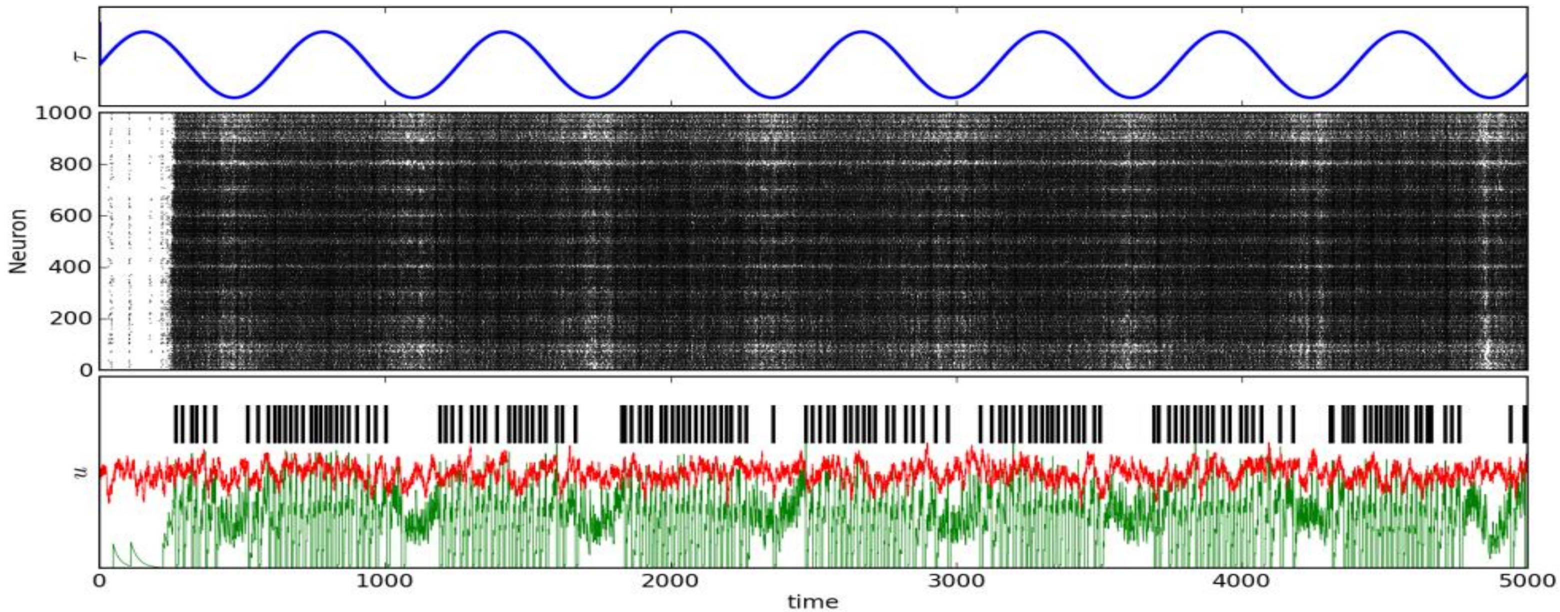
- Benuskova and Kasabov, Springer, 2007





The effect of genes on the NeuCube

Example of how a gene can affect spiking activity of a SNN reservoir

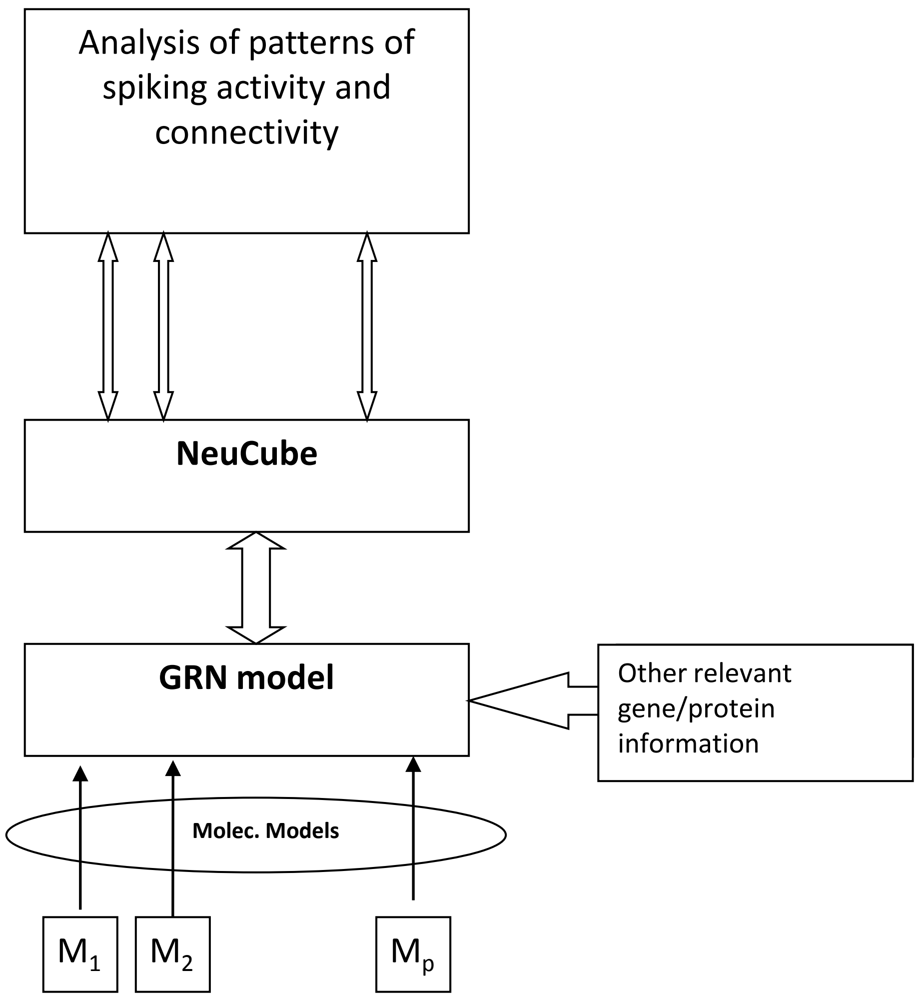


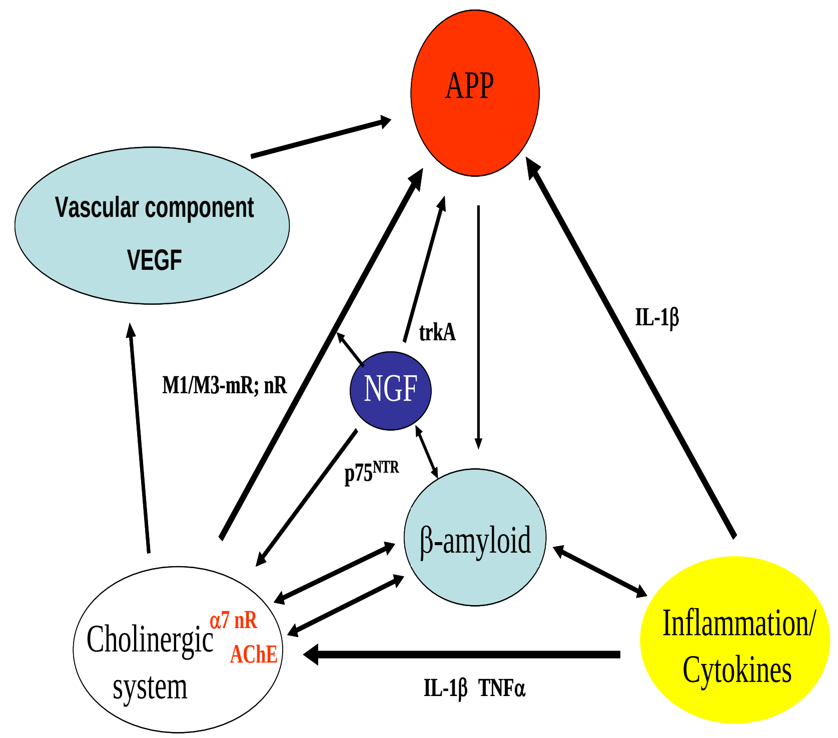
A single gene expression level over time can affect the pattern of activity of a whole cube of 1000 neurons. The gene controls the τ parameter of all 1000 LIF neurons over a period of five seconds. The top diagram shows the evolution of τ. The response of the 10000 spiking neurons is shown as a raster plot of spike activity. A black point in this diagram indicates a spike of a specific neuron at a specific time in the simulation. The bottom diagram presents the evolution of the membrane potential of a single neuron from the network (green curve) along with its firing threshold ϑ (red curve). Output spikes of the neuron are indicated as black vertical lines in the same diagram .

(from Kasabov, N., S.Schliebs and A.Mohemmed, Springer LNCS 7548, 2012).

Can AD be predicted at an early stage?

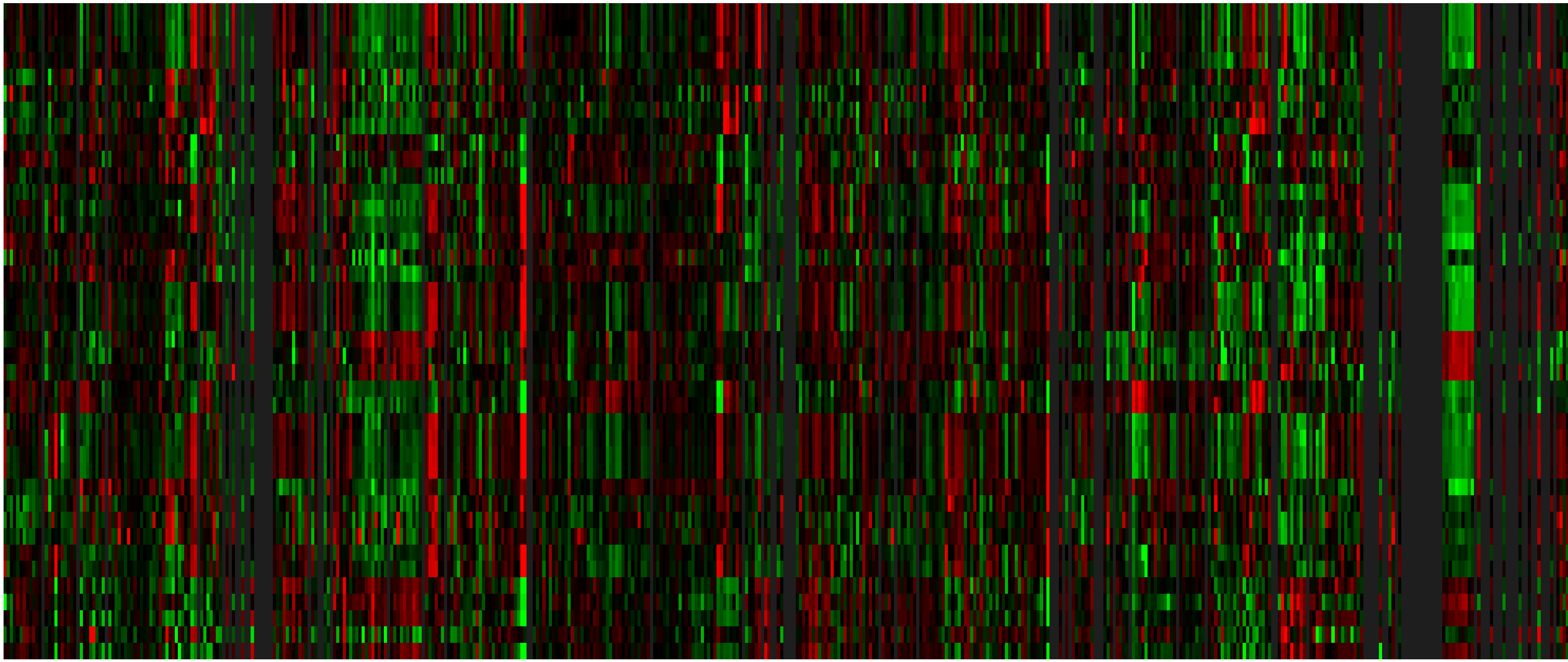
(N.Kasabov, R.Schliebs, H.Kojima, IEEE TAMD, v.3, No.4, December 2011)





Example: Gene brain map of AD patient

(from Brain Explorer – Allen Brain Atlas)



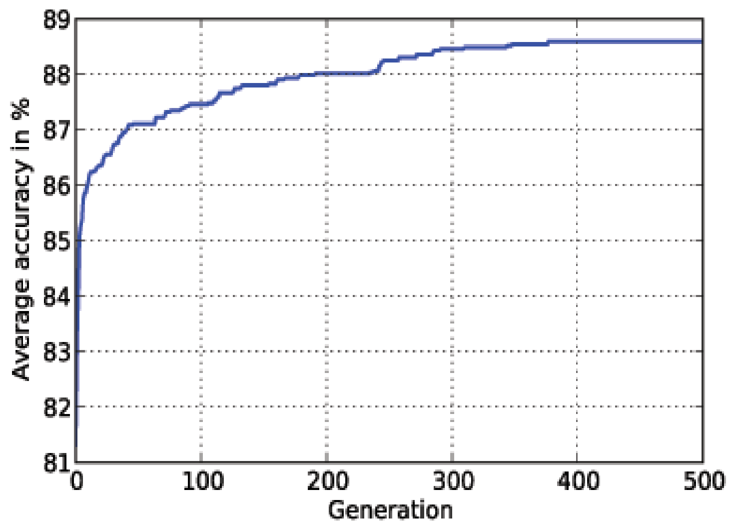
Expression of genes in the brain of AD patient: A2M A_23_P116898 ❑ A2M CUST_13981_PI416261804 ❑ A2M CUST_50_PI416408490 ❑ A2M CUST_6_PI416558205 ❑ ACE A_23_P371777 ❑ ACE A_23_P38235 ❑ ACE CUST_16698_PI416261804 ❑ ACE CUST_55_PI416408490 ❑ APBA1 A_23_P216806 ❑ APBA1 A_32_P24857 ❑ APBA1 CUST_79_PI416408490 ❑ APBB2 A_23_P10701 ❑ APBB2 A_24_P234701 ❑ APBB2 CUST_80_PI416408490 ❑ APP A_24_P314159 ❑ APP A_32_P167000 ❑ APP CUST_84_PI416408490 ❑ BACE2 A_23_P154875

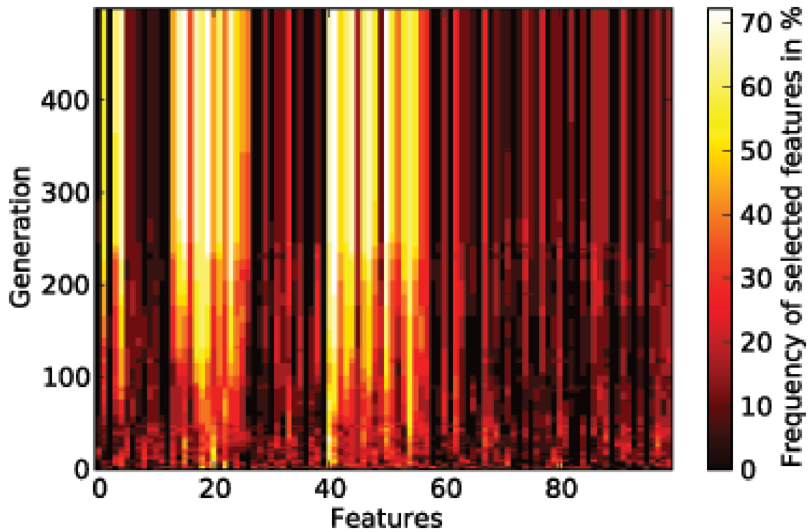
7. NeuCube Parameter Optimisation

Challenge: How to optimize the numerous spiking, probabilistic and genetic parameters.

Here we combine local learning of synaptic plasticity with global or local optimisation of parameters.

Example of using Dynamic Quantum Inspired Particle Swarm Optimisation (DQiPSO) (Hamed and Kasabov, 2011) to optimise together the features and the parameters of the reservoir-based classifier eSNN (mod, C, Sim) for a gesture recognition task – LIBRAS.

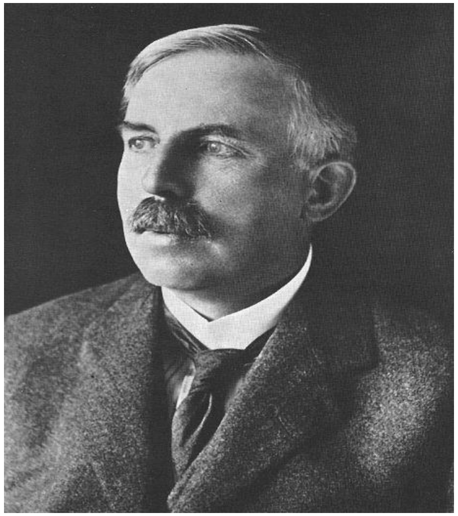




Why quantum inspired methods?

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

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



- **Quantum vectors (qu-vectors)**

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

- **Quantum gates**

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

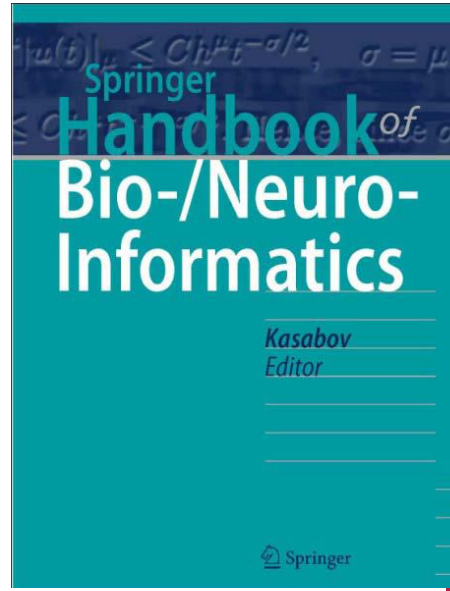
- **Why quantum inspired methods?**

- Quantum inspired EA are multiple probability density evaluation metods (Defoin - Platel et al, 2009, IEEE Tr EC)
- A single quantum bit vector represents the WHOLE problem space, each point to a certain probability
- Faster convergence to global optimum for a large dimensional space

8. Future Directions

- Implementation of NeuCube on a SNN supercomputer (e.g. SpiNNacker, U.Manchester)
- Integration of EEG and fMRI data
- New ways for brain signal recording and their representation
- Chip design for specialised applications (G.Indivery, INI/ETH/EZH)
- Applications: Engineering; BCI, Neuroprostetics; Neuroeconomics

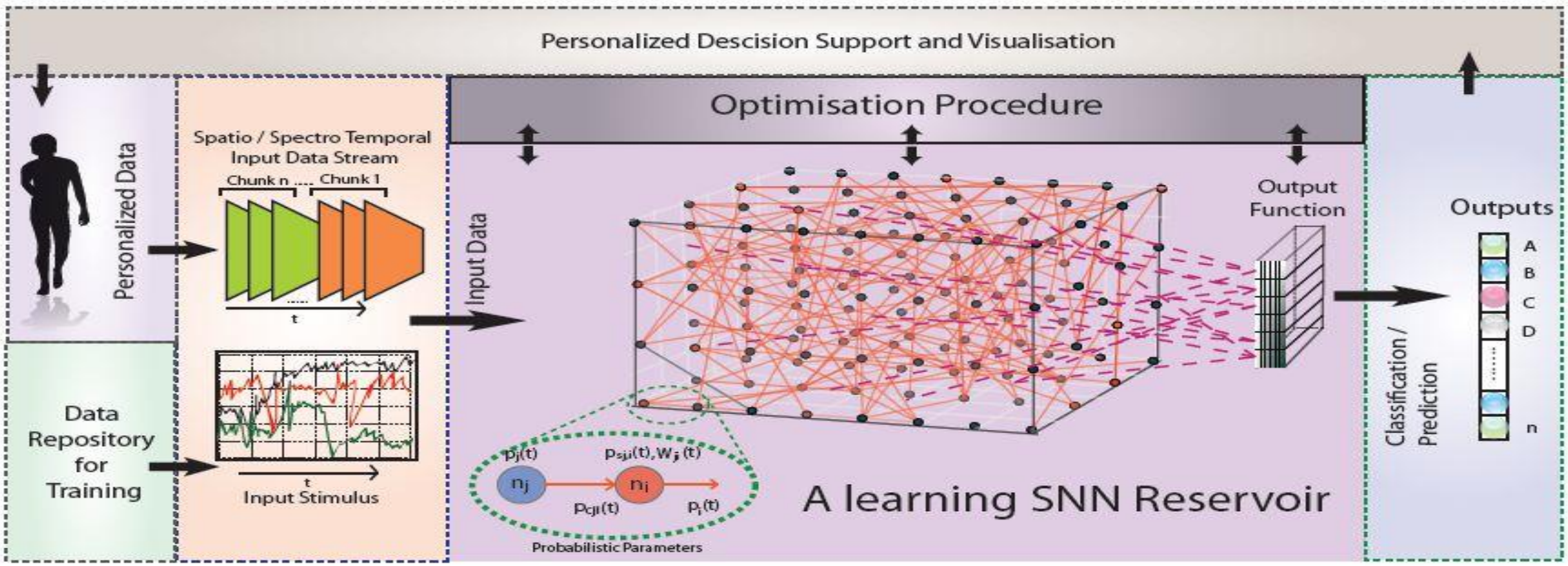
- Further interdisciplinary research in the three areas of CI, BI and NI
- The Springer Handbook of Bio-Neuroinformatics, 2013 (N.Kasabov, ed)
- The Springer Series of Bio-Neuroinformatics (N.Kasabov, ed)



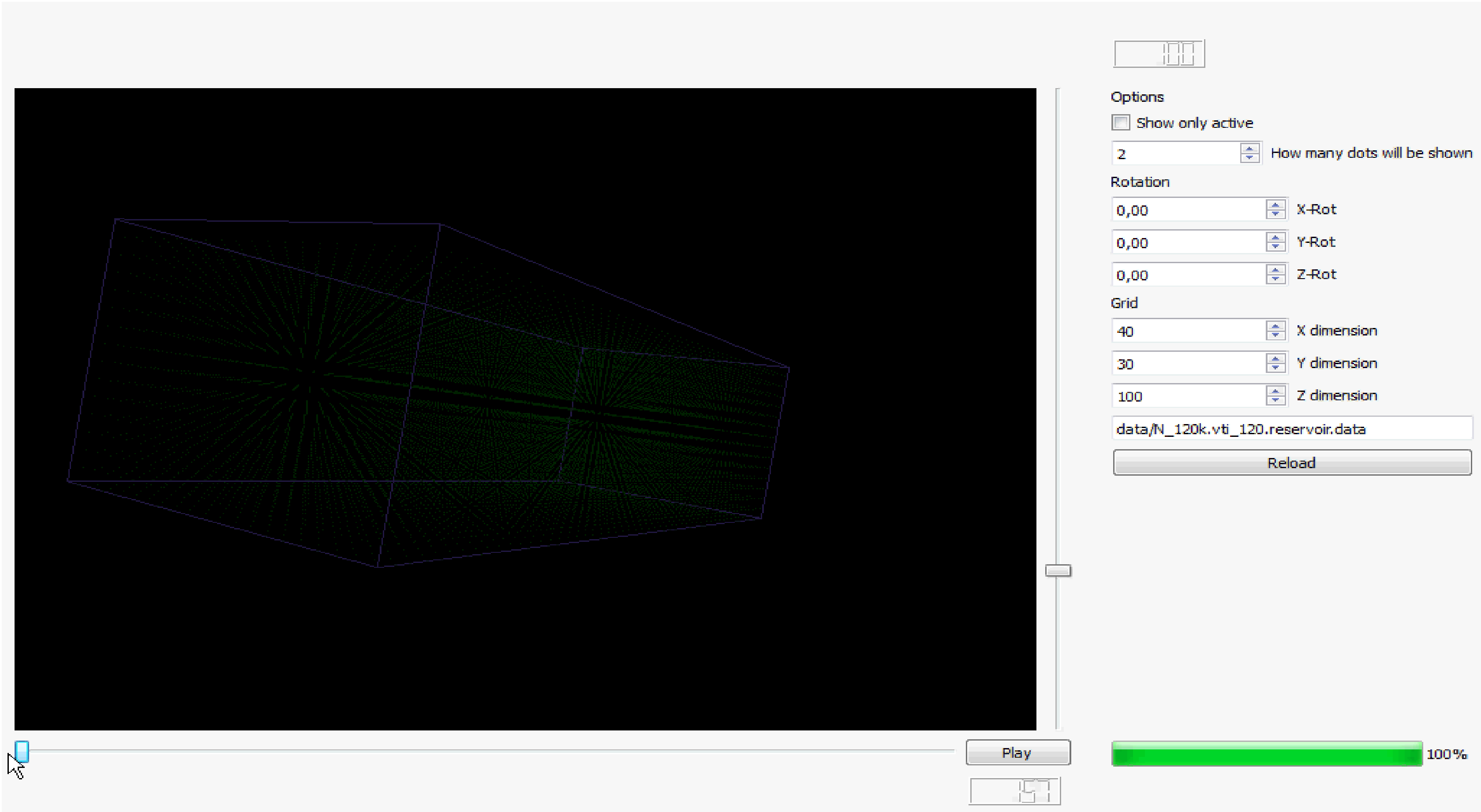
Personalised Predictive Systems

Can individual risk of stroke be predicted before the event occurrence?

N. Kasabov and R.Hu, Integrated Optimisation Method for Personalised Modelling and Case Study Applications for Medical Decision Support, *J. Functional Informatics and Personalised Medicine*, 2011



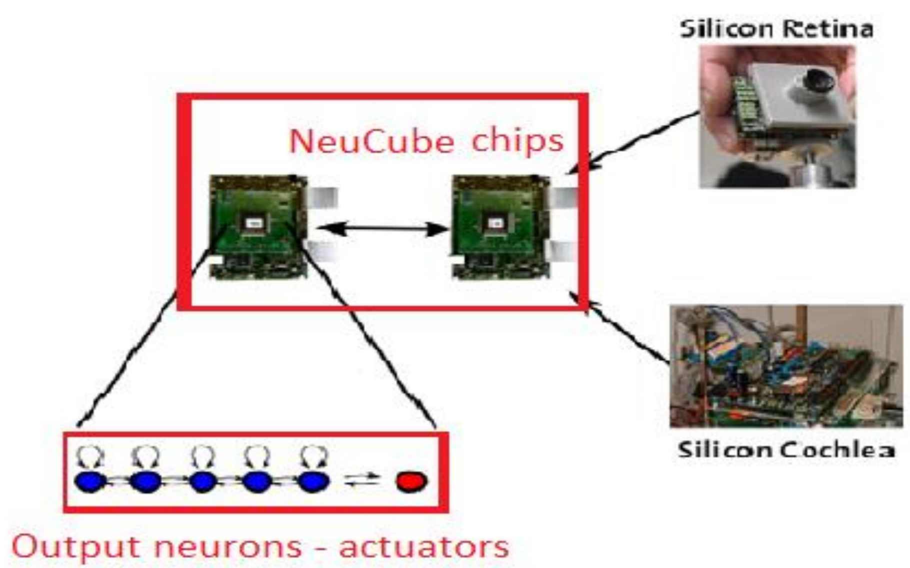
Visualisation of NeuCube spatio-temporal spiking patterns for a better understanding of brain pathways



Neuromorphic Cognitive Systems

A schematic representation of a neuromorphic cognitive system based on NeuCube chips and neuromorphic spike-based sensory devices for embedded applications (from http://ncs.ethz.ch).

Robotic systems (Hou - CAS; Kormushev - IIT)



Acknowledgement

- Knowledge Engineering and Discovery Research Institute (KEDRI, www.kedri.info), especially: Ammar Mohemmed, Nuttapod Nuntalid, Haza Nuzlu, Stefan Schliebs, Kshitij Dhoble, Jochanes Bobbs, Norhanifah Murli, Joyce D'Mello, Satoshi san.
- Marie Curie FP7 project 'EvoSpike' hosted by the Institute for Neuroinformatics at the ETH/UZH Zurich: (http://ncs.ethz.ch/projects/evospike) and Giacomo Indivery.
- The ICONIP 2012 organisers.

SEVENTH FRAMEWORK PROGRAMME

MARIE CURIE ACTIONS

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