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KNOWLEDGE ENGINEERING & DISCOVERY RESEARCH INSTITUTE
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The International Neural Network Society (INNS)

EANN 2013
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Keynote Speech

Neurocomputing for Spatio-/Spectro Temporal Pattern Recognition and Early Event Prediction: Methods, Systems, Applications

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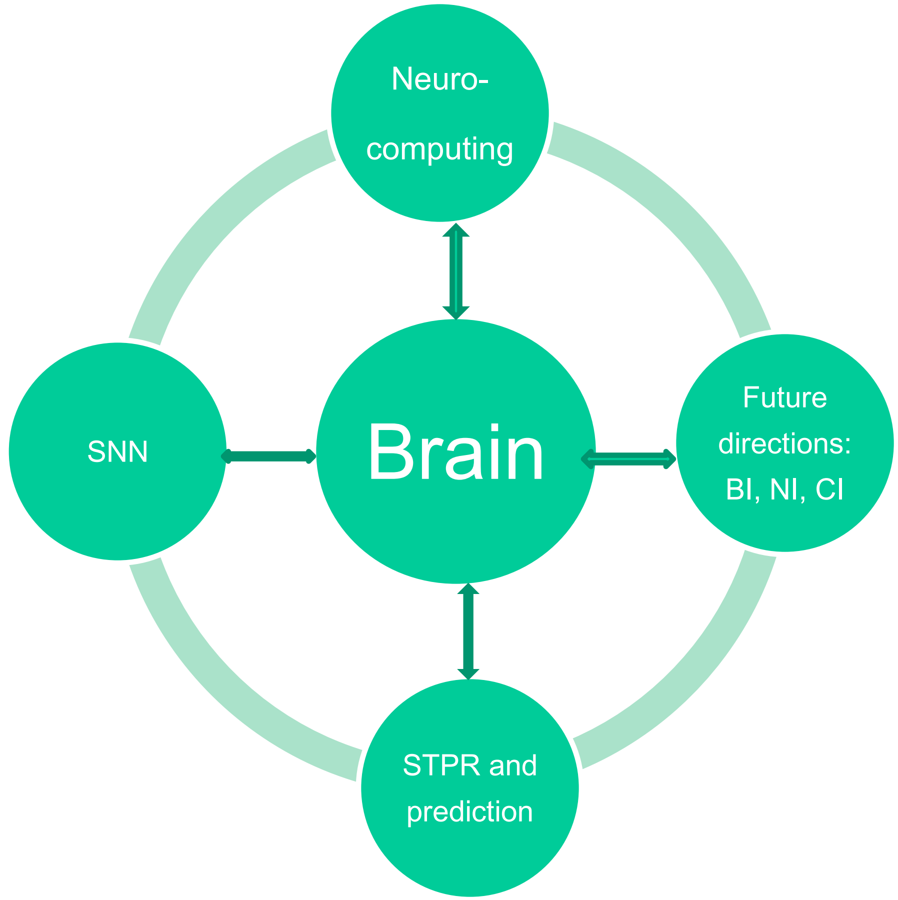

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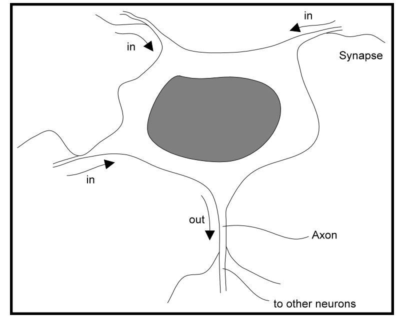
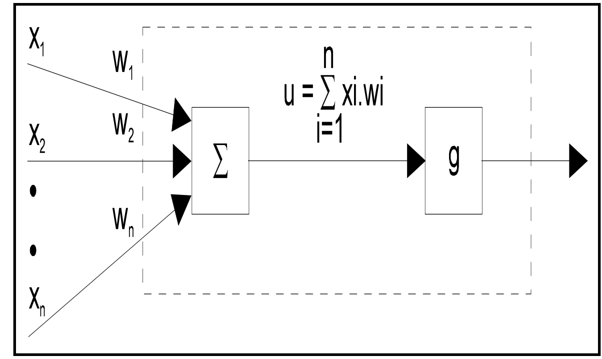
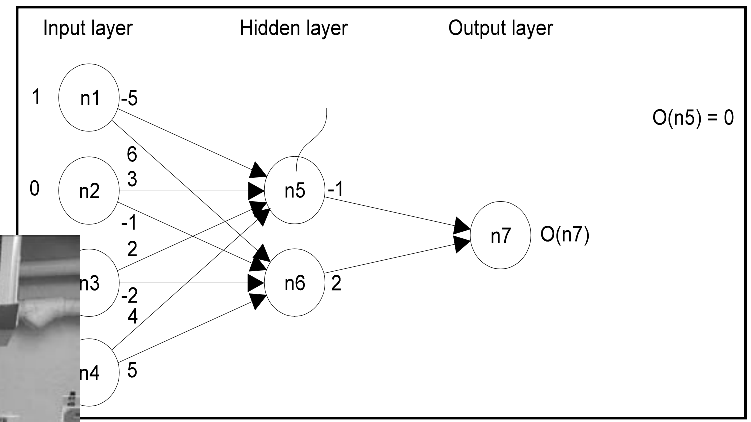
1. Neurocomputing

Neural Networks:

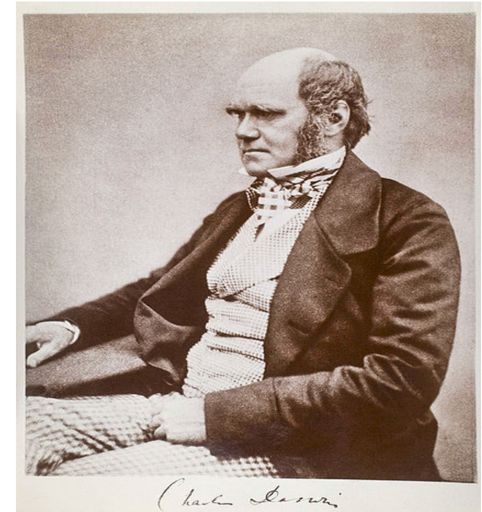
- NN are computational models that mimic the nervous system in its main function of adaptive learning.
- ANN can *learn* from data and make *generalisations*
- ANN are *universal computational models*
- 1943, McCulloch and Pitts
- 1960, Widrow and Hoff- Adelaine
- 1962, Rosenblatt - Perceptron
- 1971- 1986, Amari, Rumelhart and others, Multilayer perceptron







…Neurocomputing

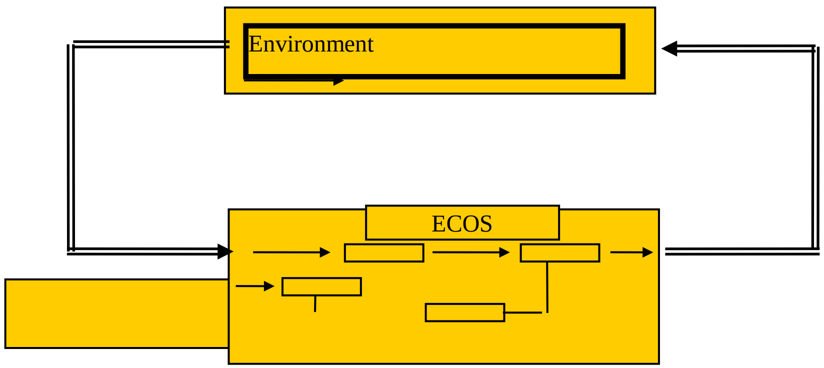


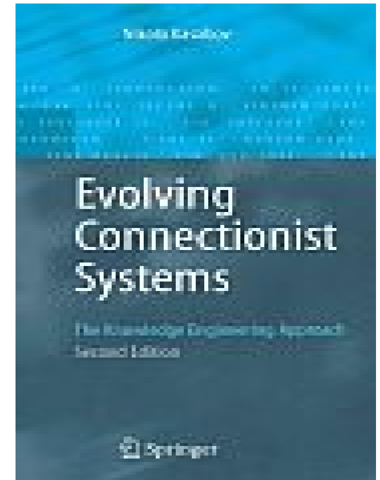
Hybrid neuro-fuzzy, neuro-evolutionary, and statistical techniques

- Evolutionary computation
- Fuzzy systems and hybrid systems (Zadeh, 1965; Yamakawa 1989; Kosko 1992; Kasabov 1992)
- Kasabov, Foundations of neural networks, fuzzy systems and knowledge engineering, MIT Press, 1996

Evolving Connectionist Systems (ECOS)

- ECOS are modular connectionist-based systems that evolve their structure and functionality in a continuous, self-organised, in on-line, adaptive, interactive way from incoming information 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, Pang, Kasabov, Polikar, Minhu Lee); evolving spiking neural networks (eSNN); computational neuro-genetic systems; quantum inspired eSNN.

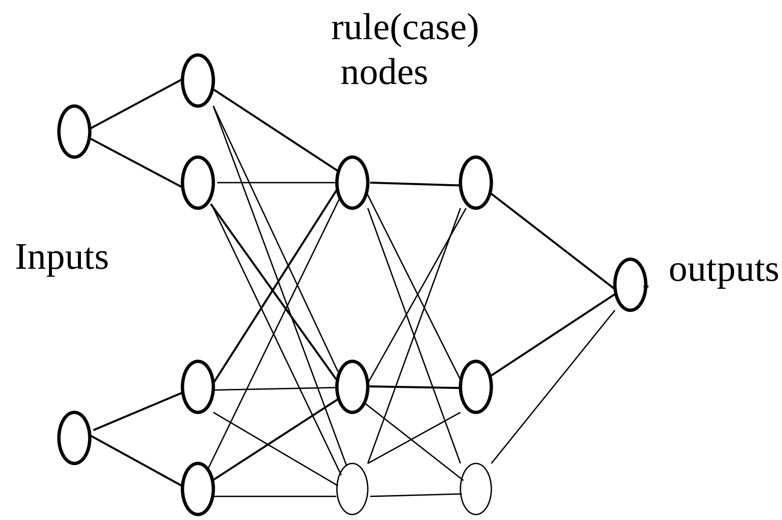
Evolving Fuzzy Neural Network (EFuNN)

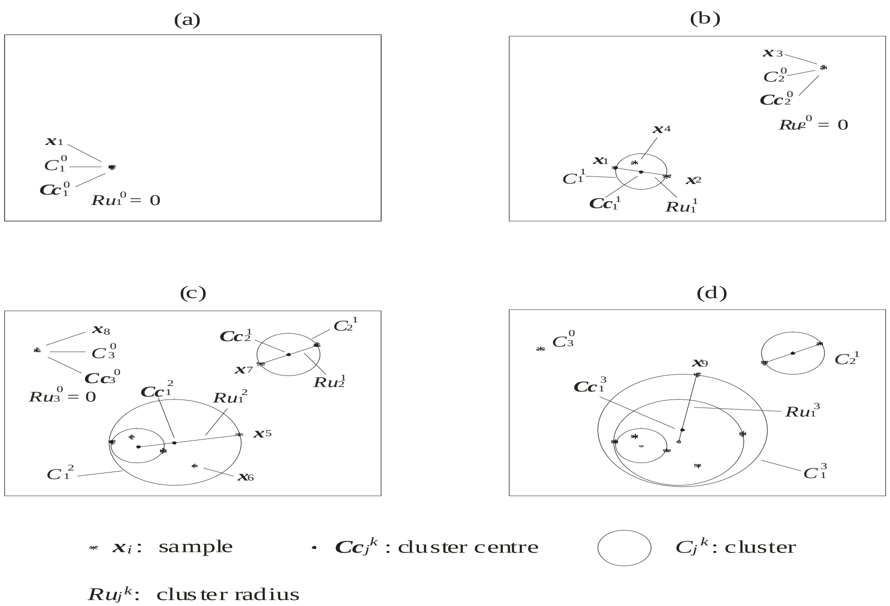
- Incremental, supervised clustering
- Input and/or output variables can be non-fuzzy (crisp) or fuzzy
- Hidden nodes evolve to capture clusters (prototypes) of input vectors
- Input weights change based on *Euclidean distance* between input vectors and prototype nodes (evolving clustering):

  $$\Delta \mathbf{w} = \mathrm{lrate} * E(\mathbf{x}, Rn)$$

- Output weights evolve to capture local output function and change based on output error.

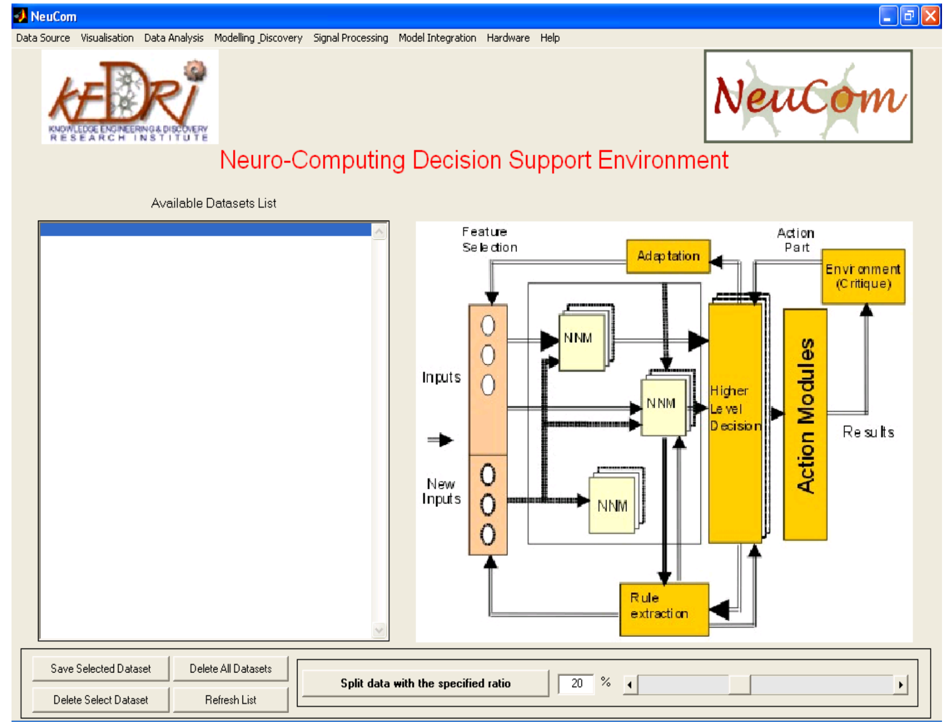
- EFuNN, N. Kasabov, IEEE Tr SMC, 2001
- DENFIS, N.Kasabov , Q.Song, IEEE Tr FS, 2002
- ECOS Toolbox available in MATLAB
- NeuCom Software available: www.kedri.info





NeuCom: A Software Environment for NeuroComputing, Data Mining and Intelligent System Design (www.theneucom.com)

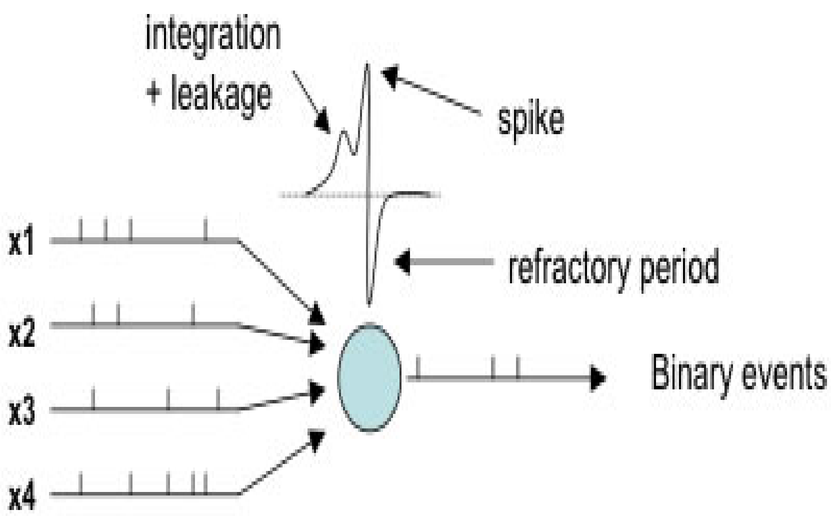
- A generic environment, that incorporates 60 traditional and new techniques for intelligent data analysis and the creation of intelligent systems, including:
  - Statistical methods
  - Neural networks
- Methods for feature selection
- Methods for classification
- Methods for prediction
- Methods for knowledge extraction
- Fast data analysis and visualisation
- Fast model prototyping
- A free copy available for education and research from: www.theneucom.com
- DENFIS for prediction
- ECF for classification



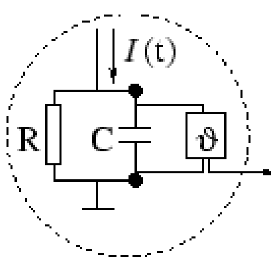
2. Spiking Neural Networks

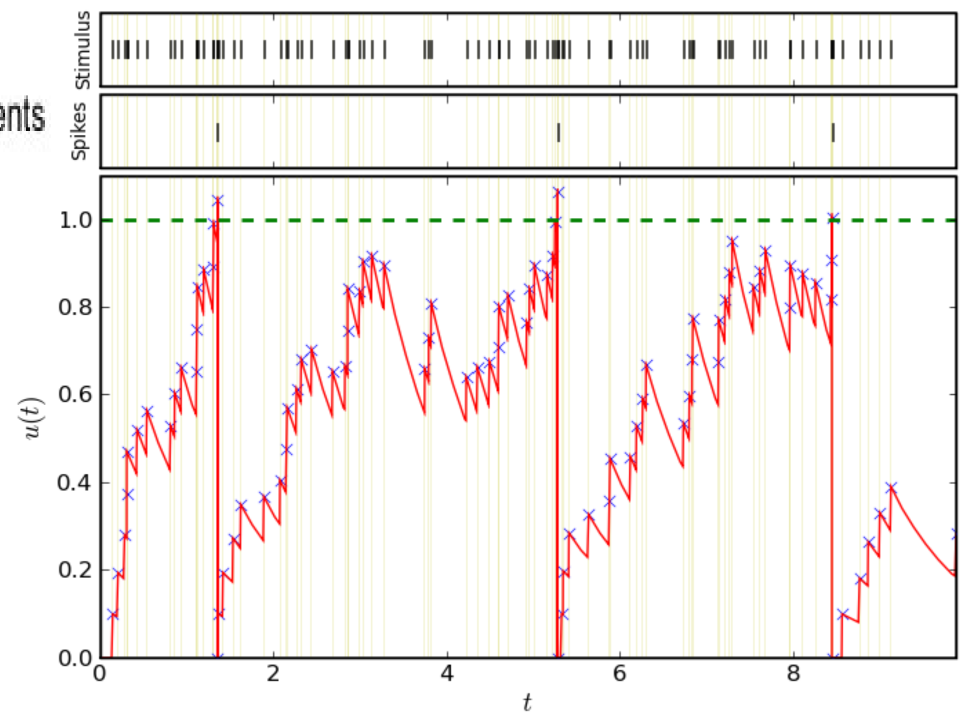
Models of spiking neurons: (Hodgkin-Huxley 1952; Abbott, 2000; Maas, Izhikevich; other)

Most popular is the Leaky Integrate and Fire Model (LIF)



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

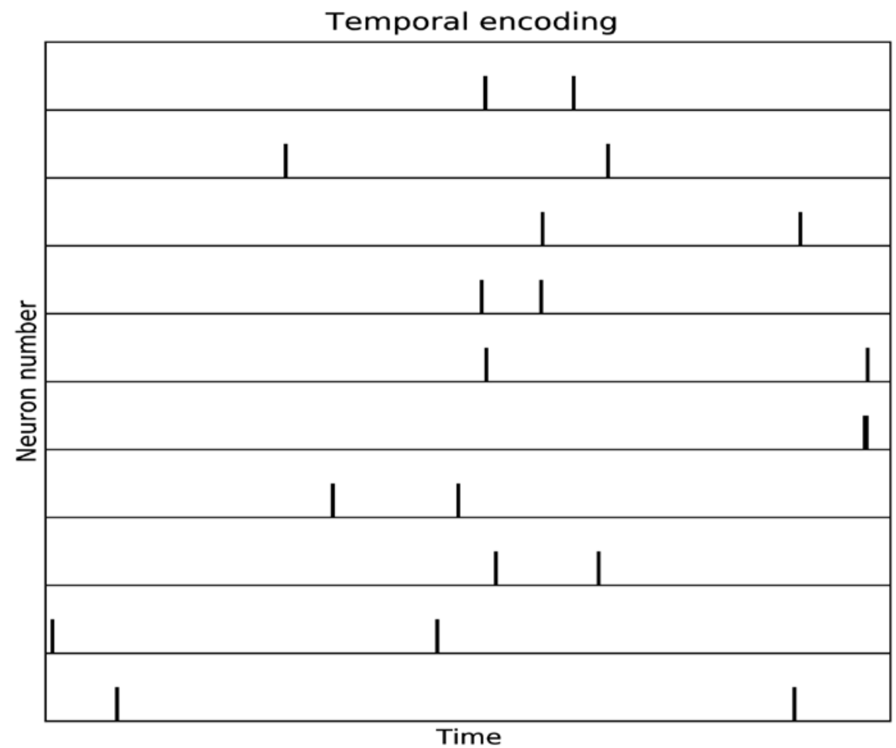




Representing information as spikes: Rate vs time-based

- 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.

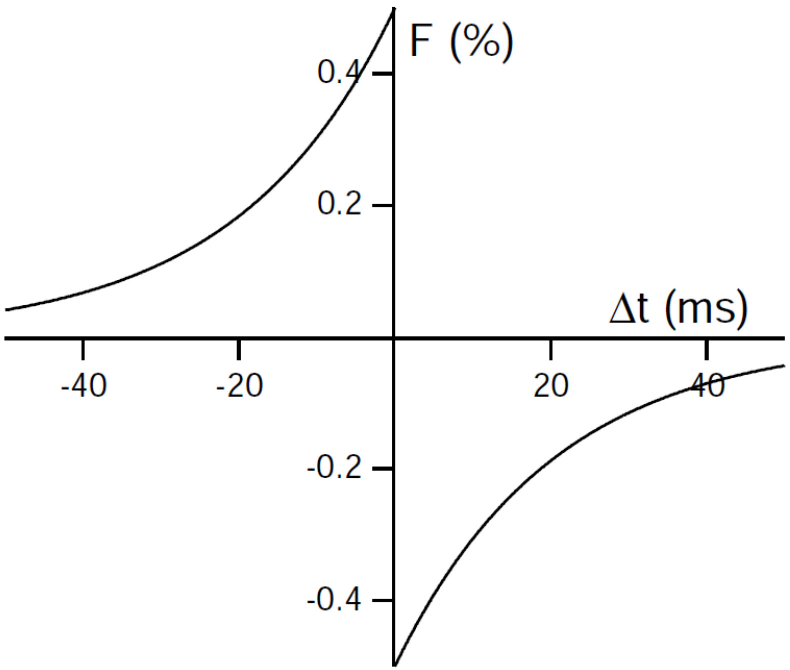


Methods for learning in SNN:
Spike-Time Dependent Plasticity (STDP)
(Abbott and Nelson, 2000).

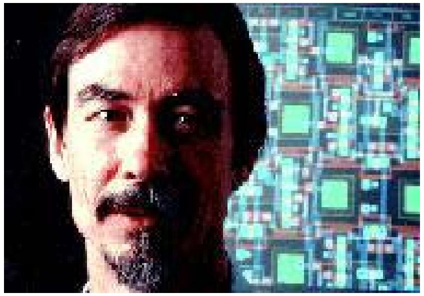
- Hebbian form of plasticity in the form of long-term potentiation (LTP) and depression (LTD)
- Effect of synapses are strengthened or weakened based on the timing of pre-synaptic spikes and post-synaptic action potential.
- Through STDP connected neurons learn consecutive temporal associations from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

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

Δt=tpre -tpost



Progress in neuromorphic computation



Hodgin- Huxley model (1952)

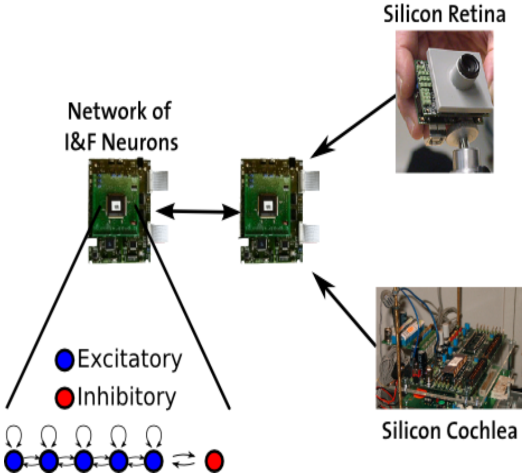
Carver Mead (1989): A hardware model of an IF neuron:
The Axon-Hillock circuit;

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



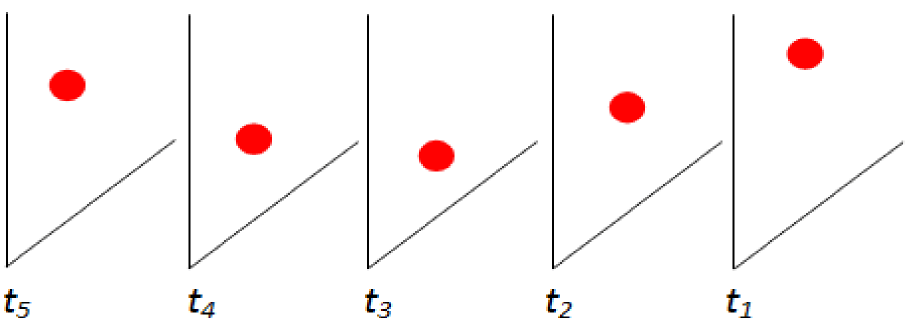
The challenge: Technology is available, but how do we use it for **integrated spatio-temporal data** modelling and STPR?

3. Spatio/Spectro-Temporal Pattern Recognition

- Most real world data is spatio- or spectro- temporal.
- In STPR problems spatial and temporal components of the information are interrelated.
- Examples of spatio-temporal data and related problems are:

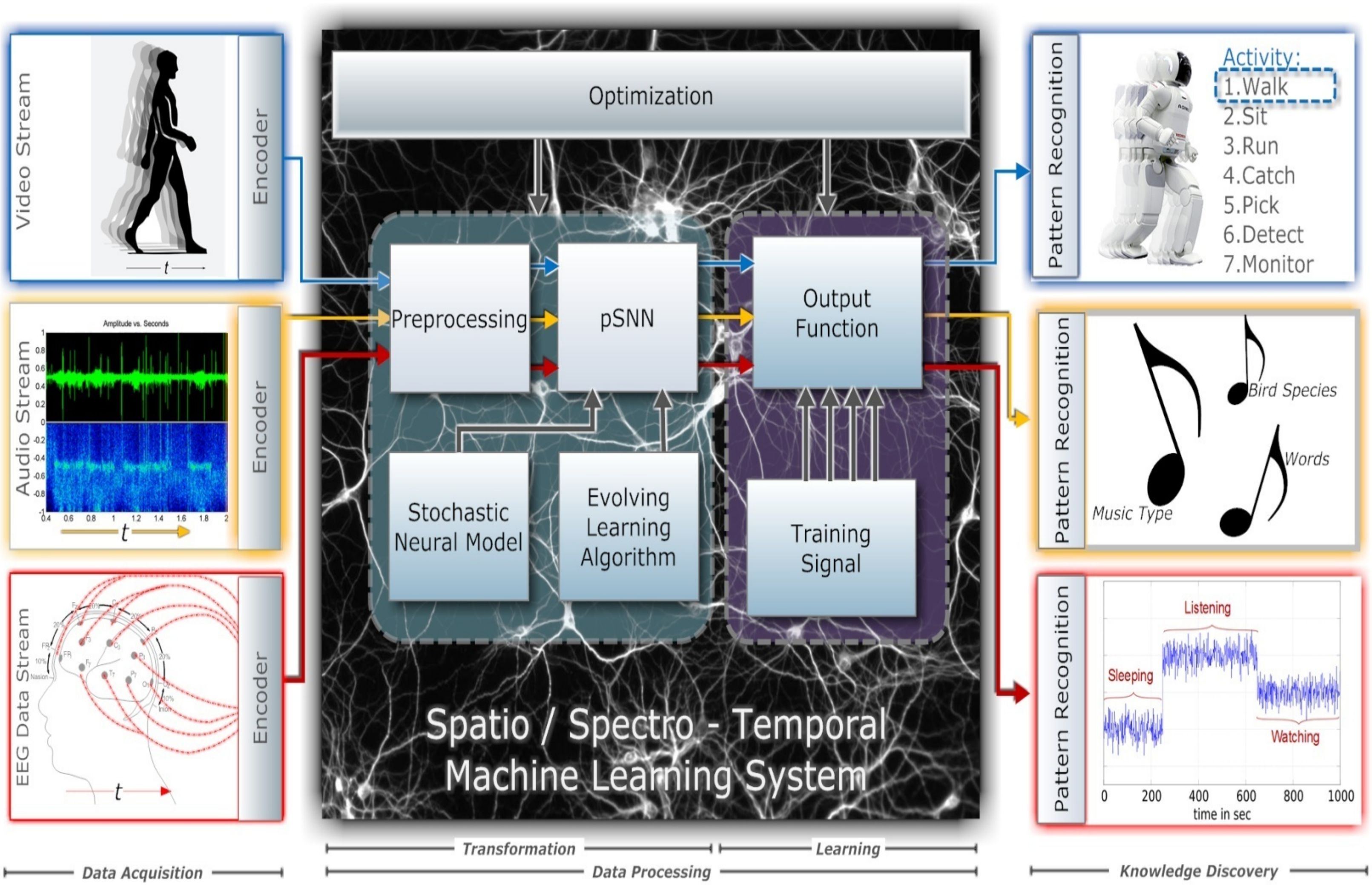
  a) Object movement recognition from video data
  b) Audio/video data modelling
  c) Multisensor temporal data integration
  d) Brain signals (EEG, MEG, fMRI)
  e) Brain- computer interfaces
  f) Motor control for prosthetics
  g) Ecological and environmental data, e.g. earthquake prediction
  h) Robot control
  i) Cyber-security data

- Goal: Developing new methods

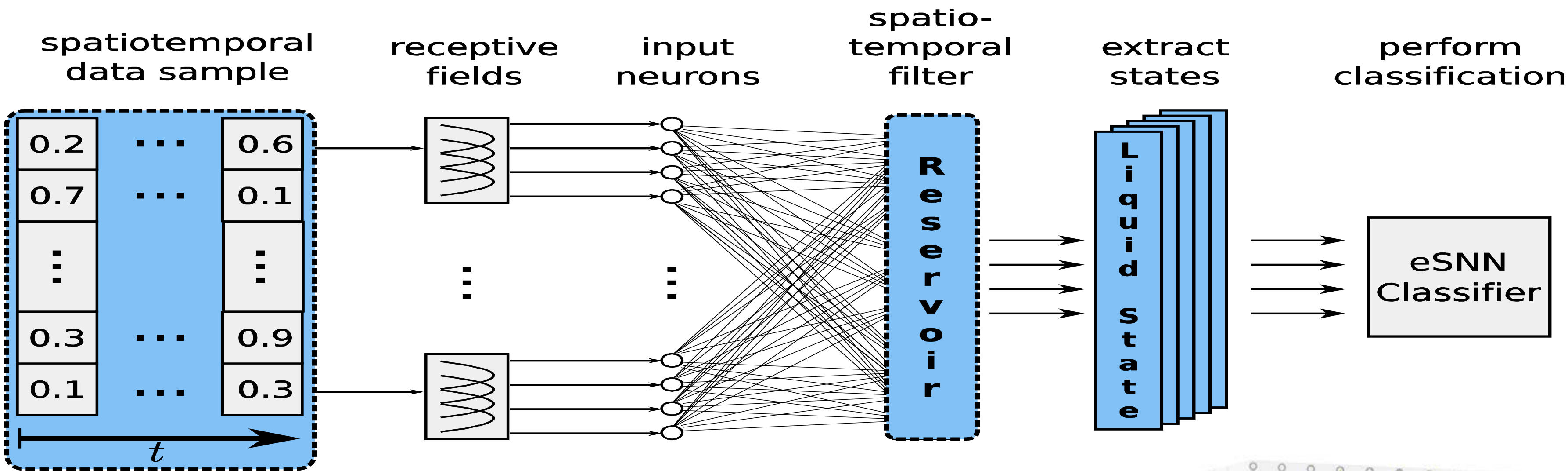


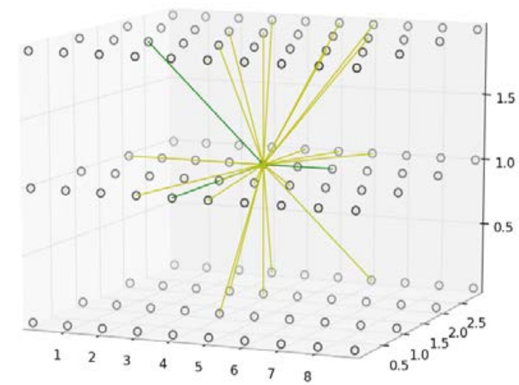
Spatio-temporal input data

The EvoSpike Project: EU FP7Marie Curie (http://ncs.ethz.ch/projects/evospike)



Reservoir-based eSNN for STPR





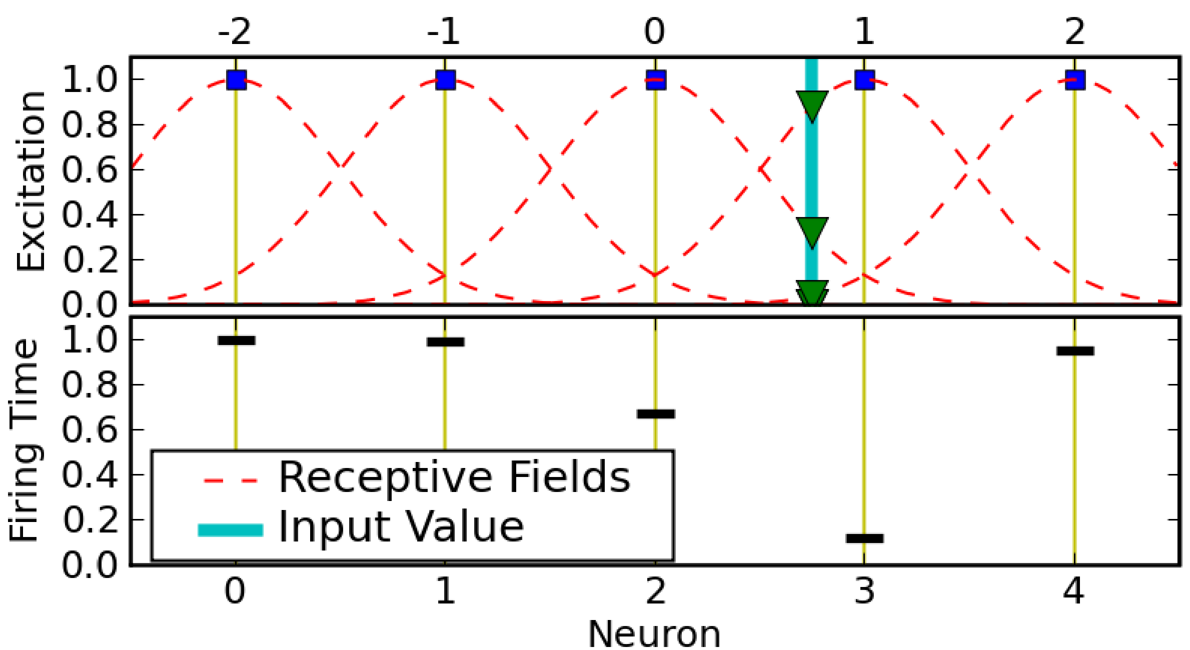
- *Maass, W., Natschl ̈ager, T., Markram, H.: Real-time computing without stable states, Neur. Comp. 14(11),2002;*
- Input (feature) neurons connected to part of the LSM
- Output neurons connected to part of the LSM
- LSM recurrent connections, e.g. small world connections
- Excitatory 80%, Inhibitory 20%
- Learning in LSM: STDP; spike time delay ....???
- Polychronization (Izhikevich): ‘opening the box’?

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

Encoding input data into spikes

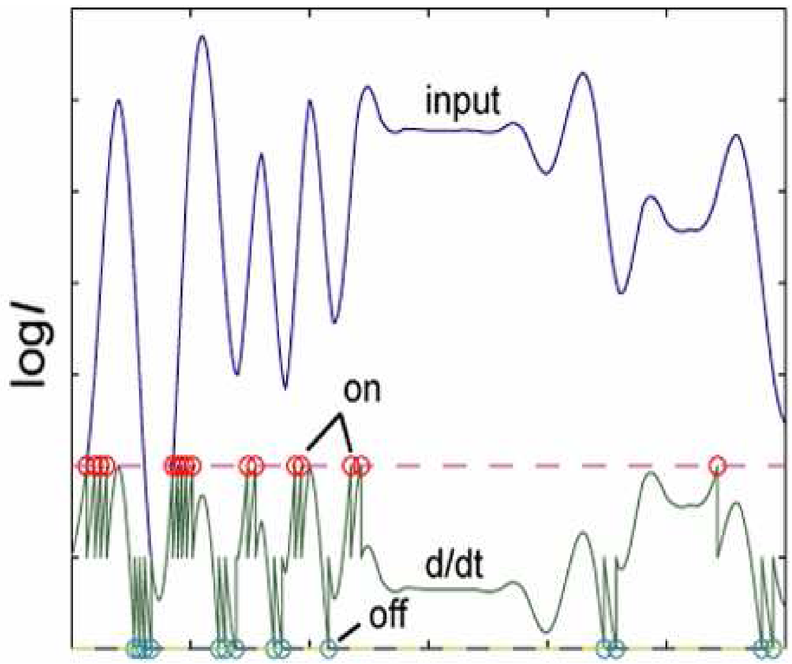
Rank Order Population Encoding

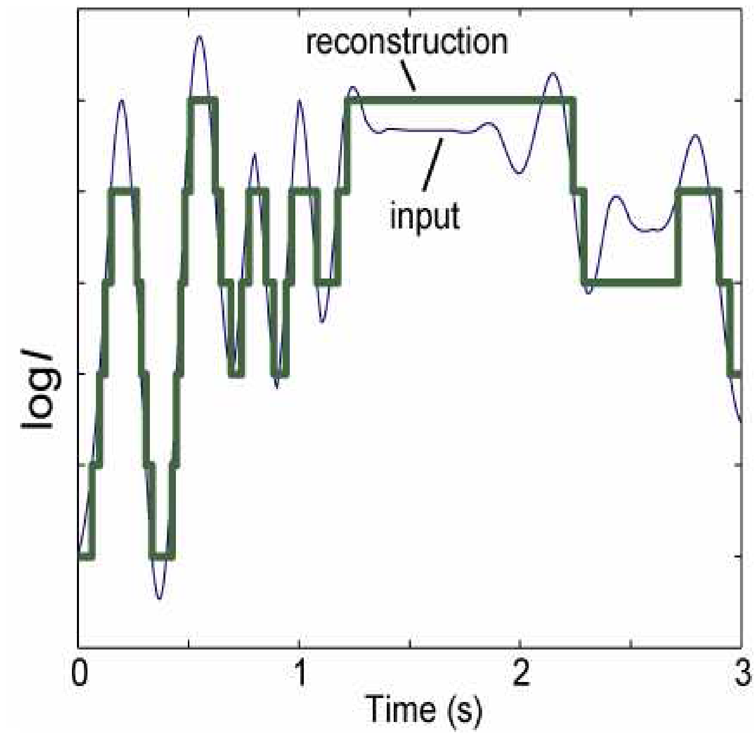
- Distributes a single real input value to multiple neurons and may cause the excitation and firing of several responding neurons
- Implementation based on Gaussian receptive fields introduced by Bothe *et al* . 2002



Address Event Representation (AER) Encoding

A spike is generated only if a change in the input data occurs
Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128
Silicon Cochlea (Shih-Chii Liu, INI, ETH/UZH, Zurich)





Evolving SNN (eSNN) as a classifier

- 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.

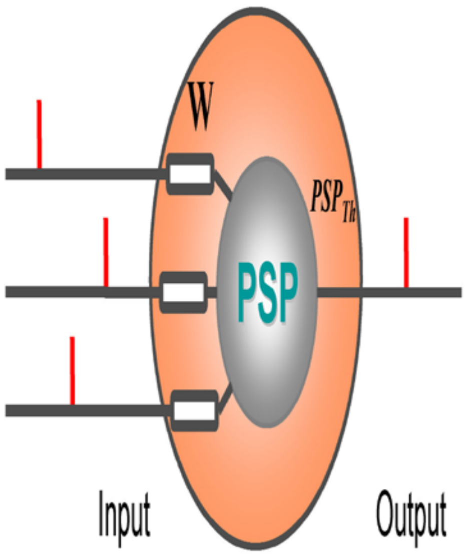
  d) Update the corresponding threshold ϑ:

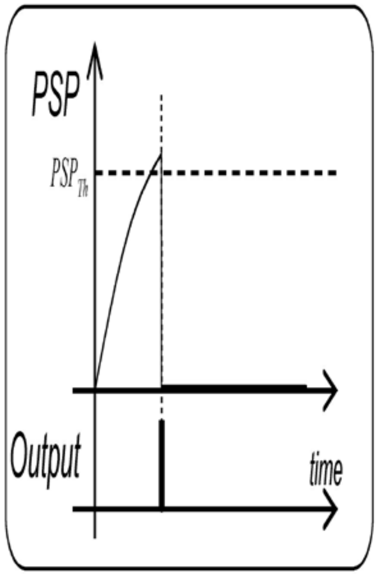
$$\vartheta \Leftarrow \frac{\vartheta_{new} + N\vartheta}{1+N}$$

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

The 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

Dynamic Evolving SNN (deSNN)

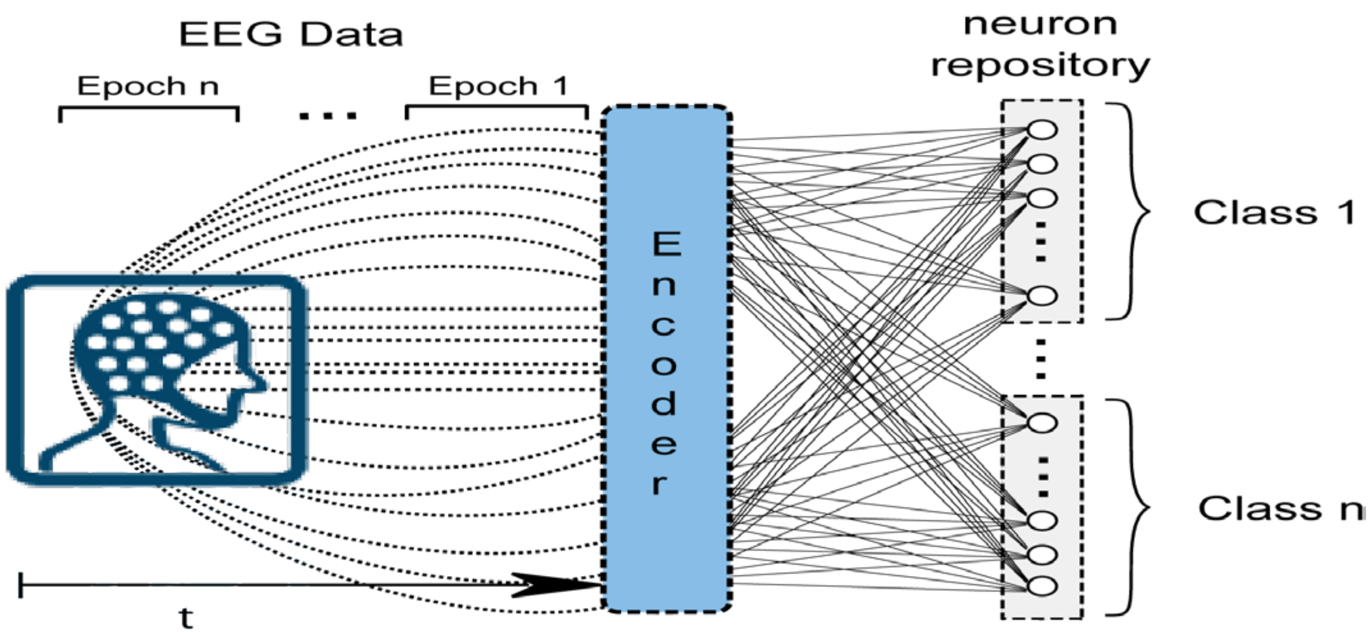
(Kasabov, Dhoble, Nuntalid, Indivery, Neural Networks, 2013)

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

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

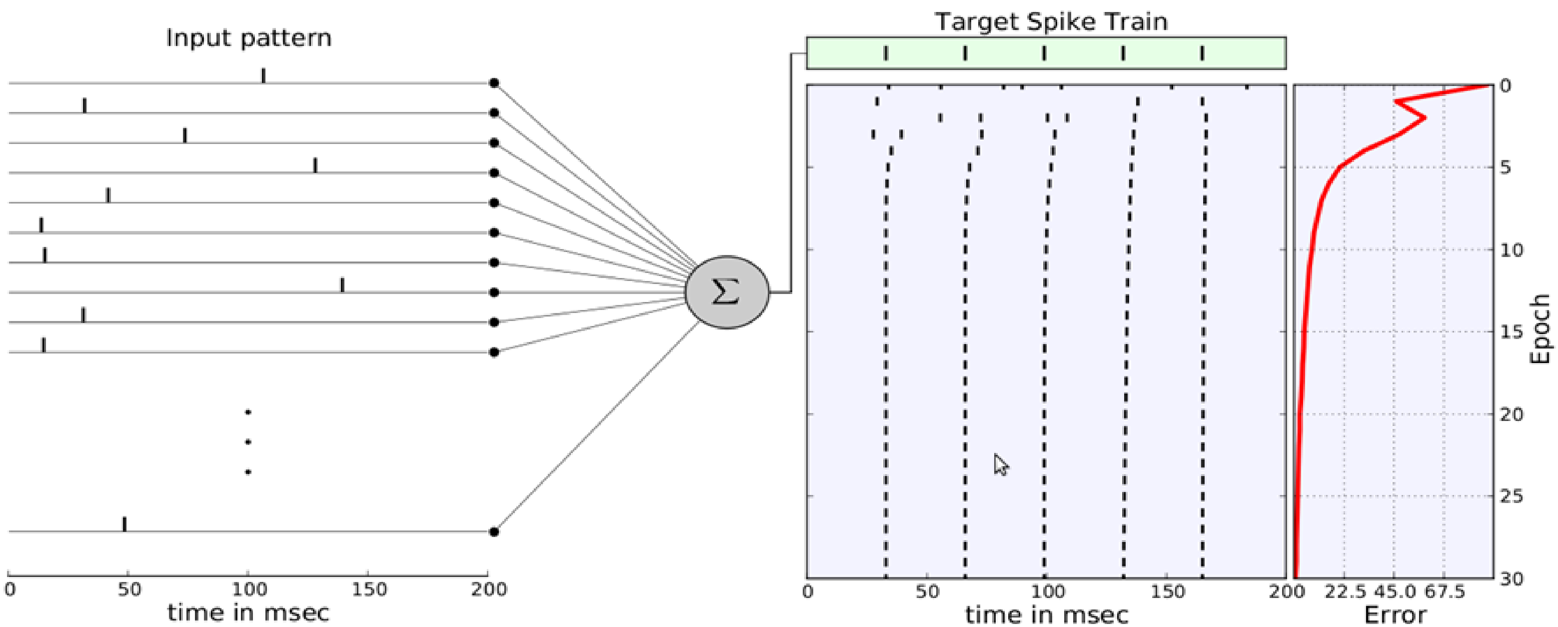
(b) SDSP for learning further input spikes at a synapse.

- A new output neuron is added to a respective output repository for every new - input pattern learned. Neurons may merge.
- The figure below shows the deSNN architecture on a case study for EEG STPR.



SPAN: Spike Pattern Association Neuron and the Delta Rule

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

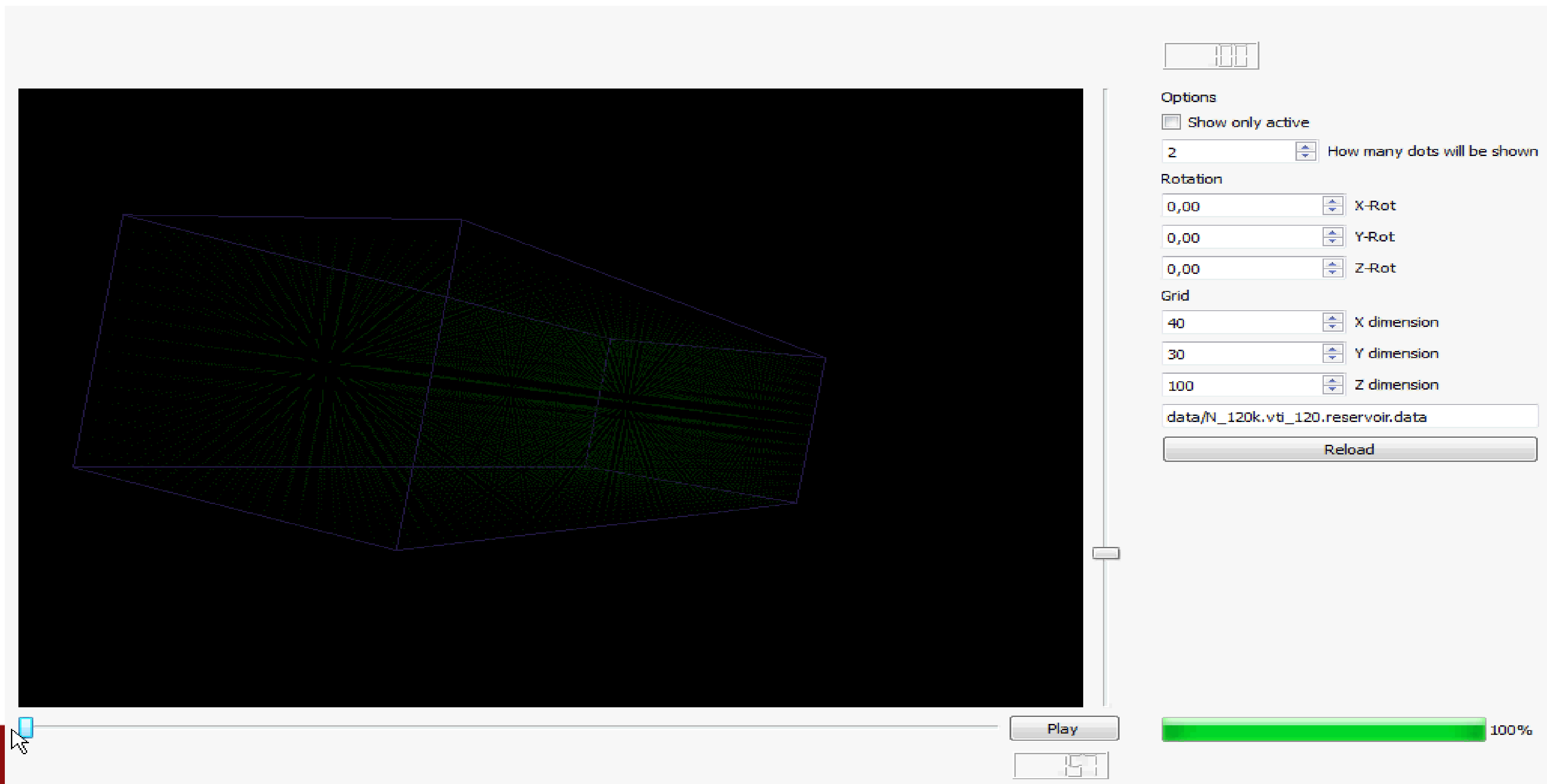


A single output neuron is trained to respond with a temporally precise output spike train to a specific spatio-temporal input.

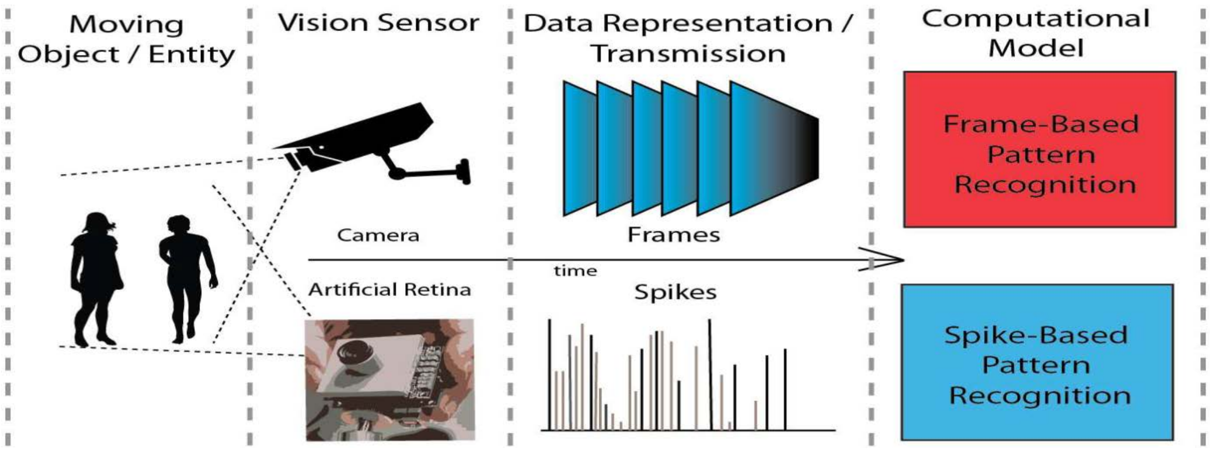
Spike pattern association neuronal models: SpikeProp; ReSuMe; Tempotron; Chronotron.

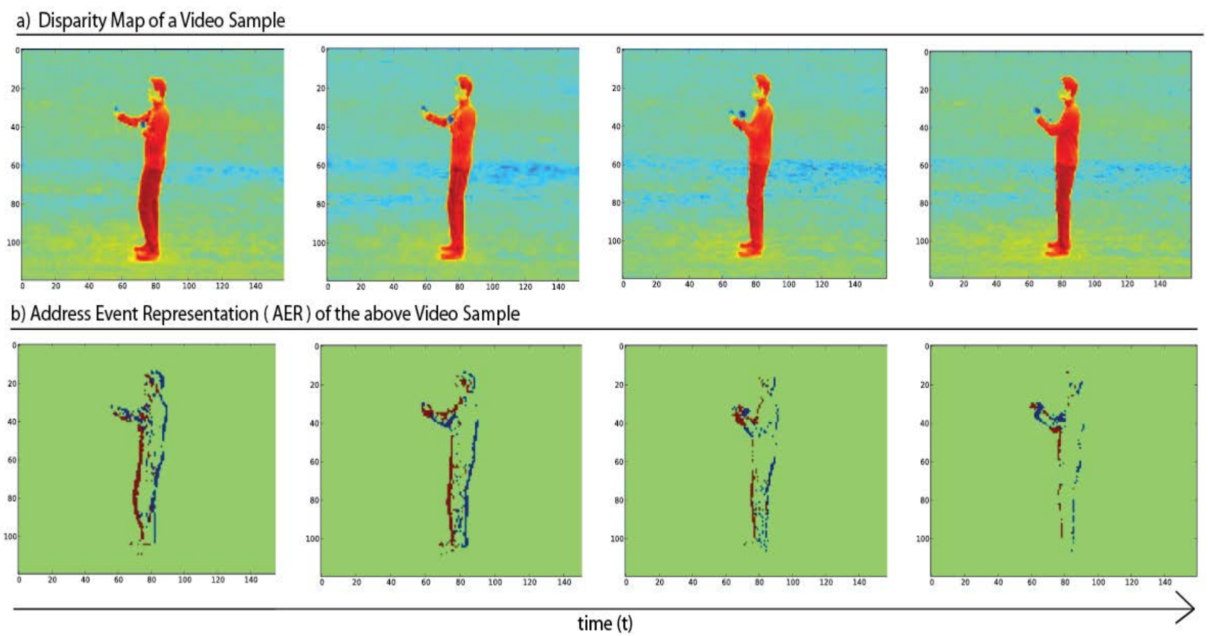
The EvoSpike Simulator

A collection of modules and functions written in Python using functions from Brian library:
- Converting continuous-value input data into spike trains;
- SNN for spatio-temporal pattern recognition (SPAN, deSNN, LSM deSNN, …);
- Knowledge extraction from trained eSNN;
- Presenting results and visualisation of learning processes ;
- Connecting software modules with neuromorphic hardware.



Moving object recognition – frame-based vs AER





Muti-sensor Integrated Stream Data Classification

- Surveillance
- Medical devices
- Ecological and climate data
- Sport
- Example: classification of horse riding activities

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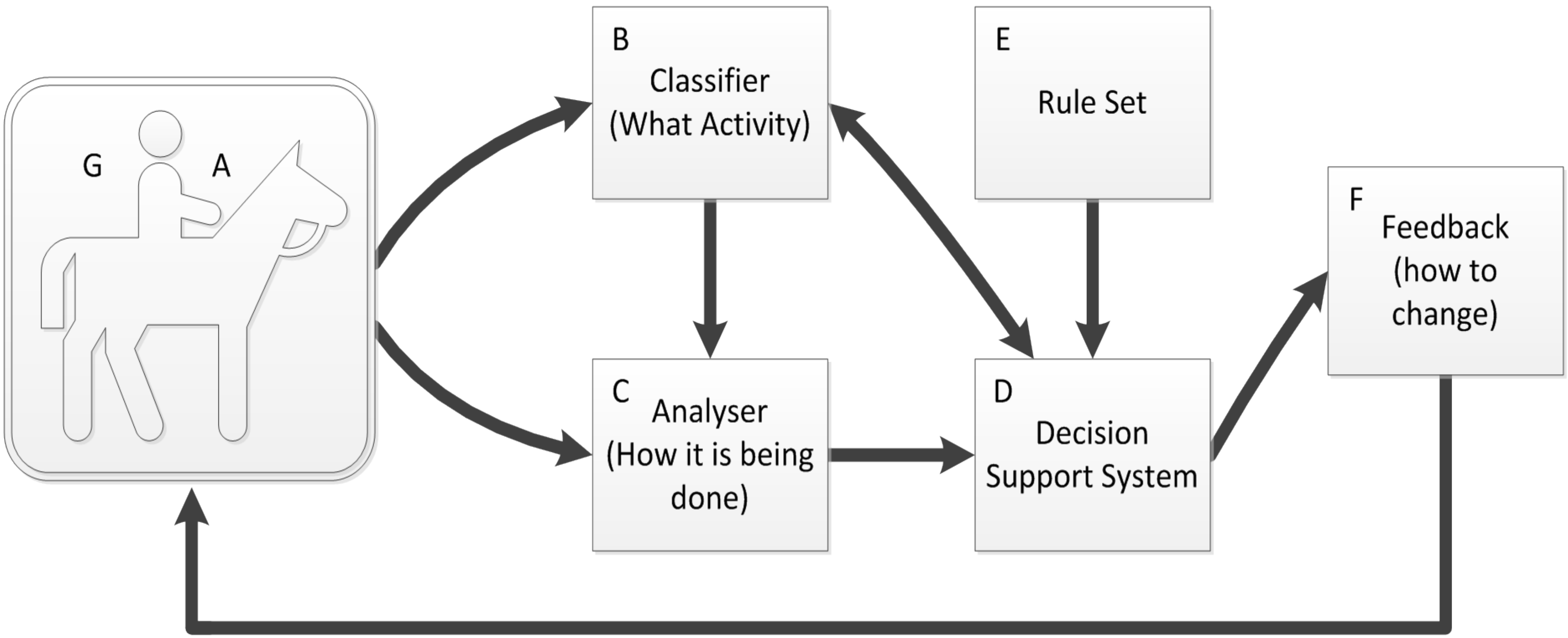
Case study: W*earable Coach (EANN 2013)*

A - Sensors
G - Feedback

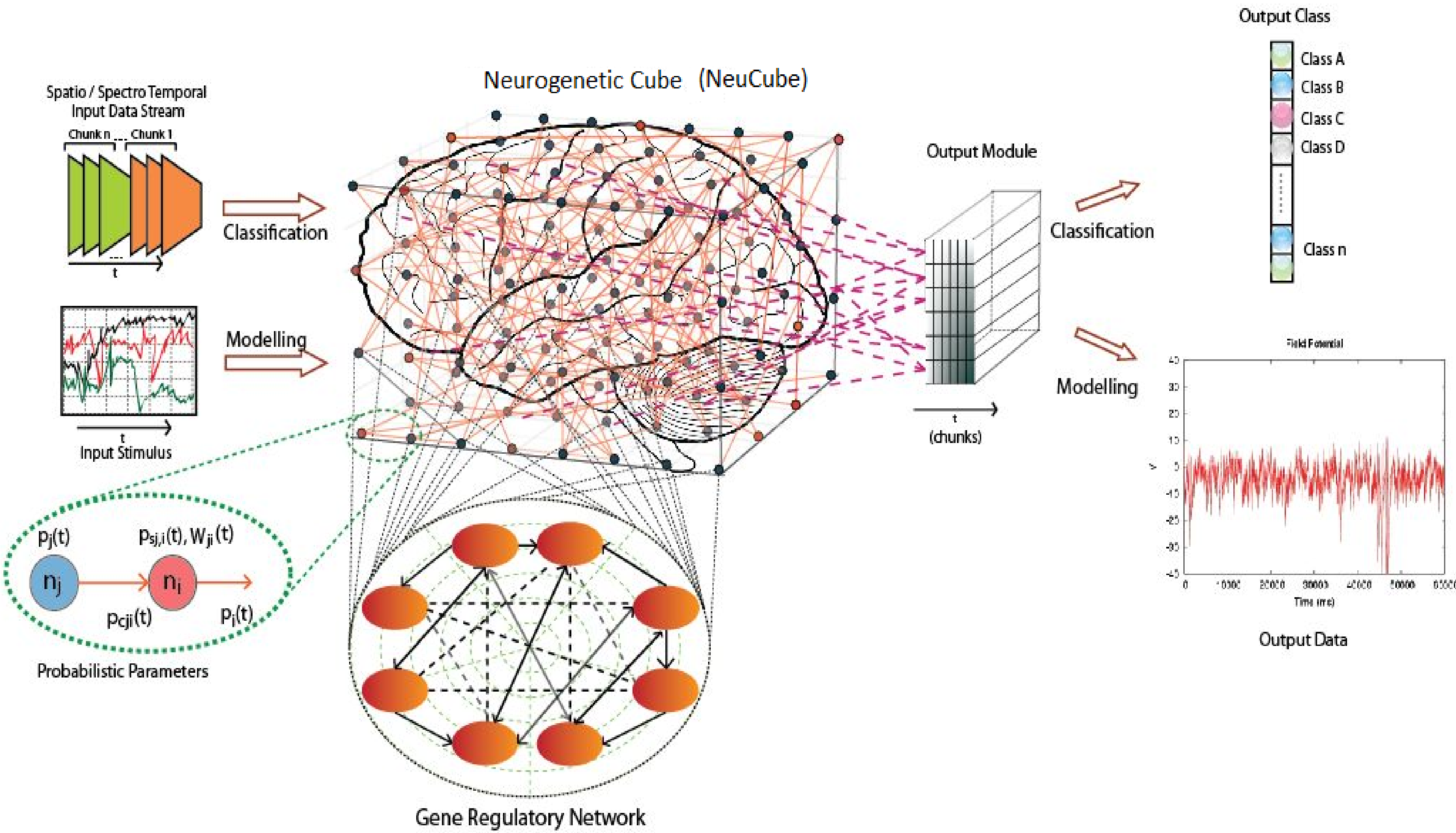


Adaptive, autonomous robot control

(e.g. work by P.Kormushev –IIT, Genoa; R.Duro – U. la Coruna, P.Angelov – U.Lancaster; KIT Japan; U.Ulster, NASA,)

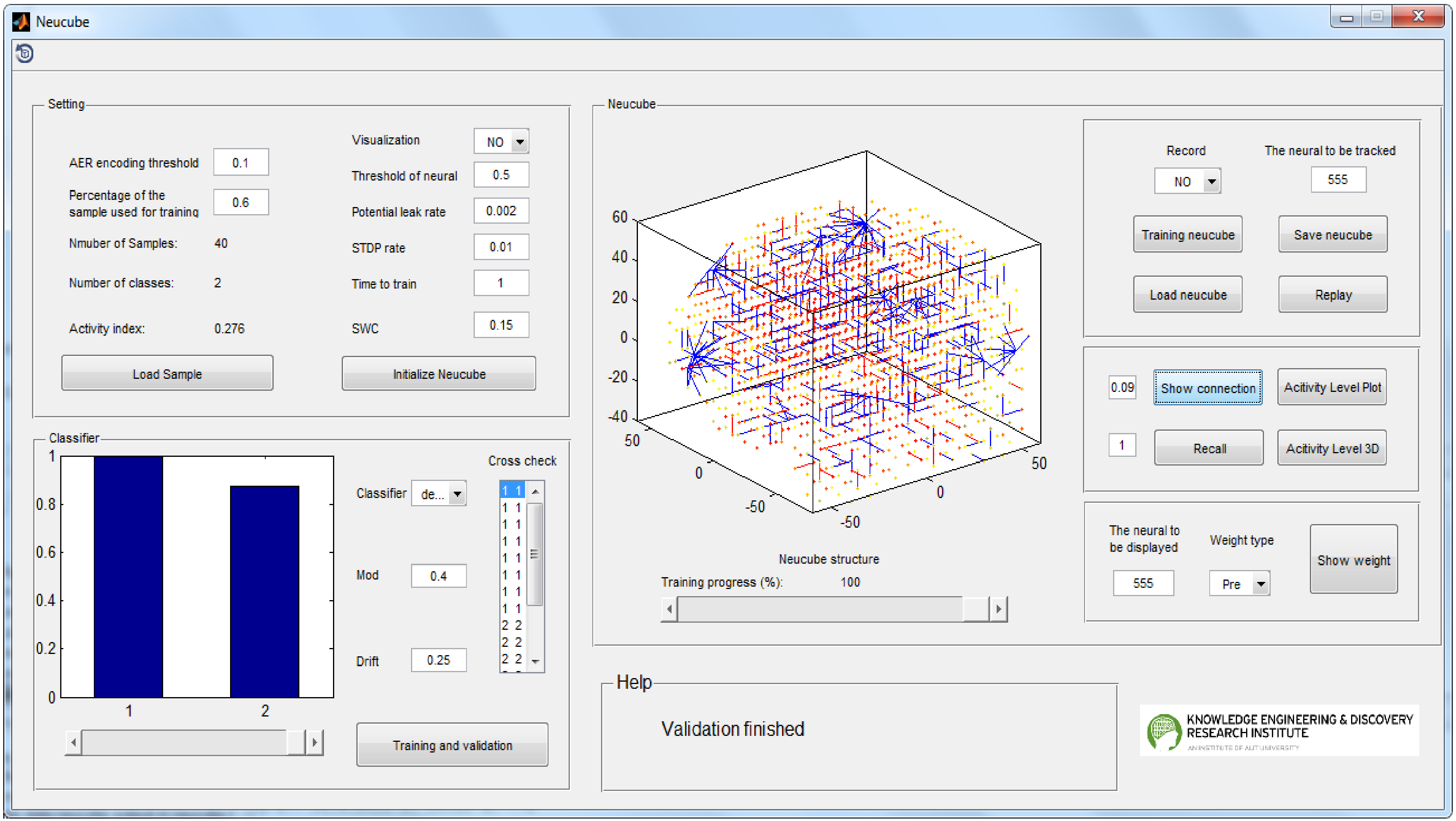
The NeuCube Architecture for Integrated Brain Data Modelling and brain STPR

(Kasabov, Springer LNAI 7477, 2012; Kasabov, NN 2013)



NeuCube Implementation

- Module input data encoding into spikes (e.g. AER)
- Module 3D reservoir (e.g. 1471 neurons)
- Module classifier (e.g. deSNN)



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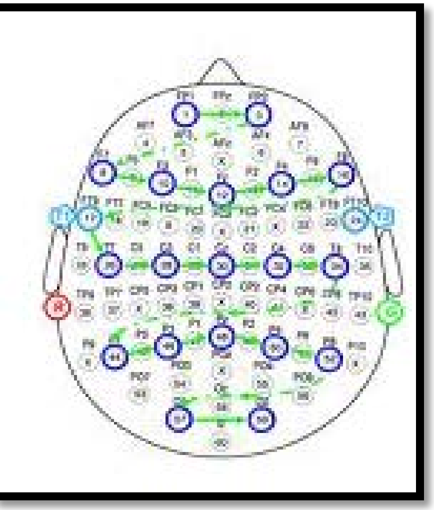
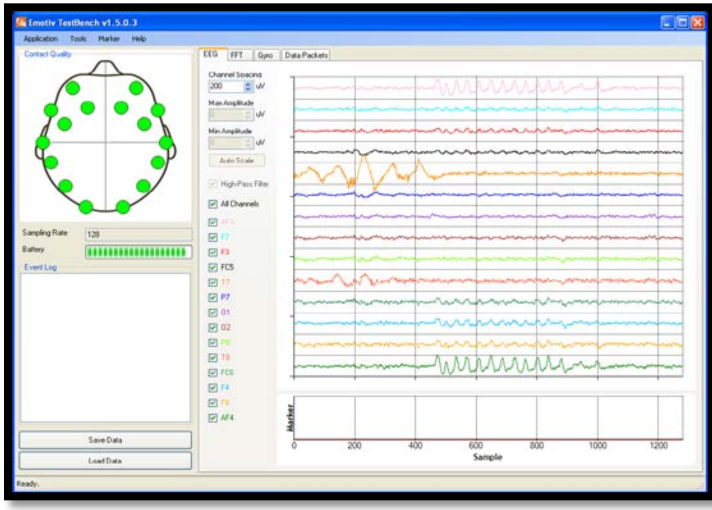
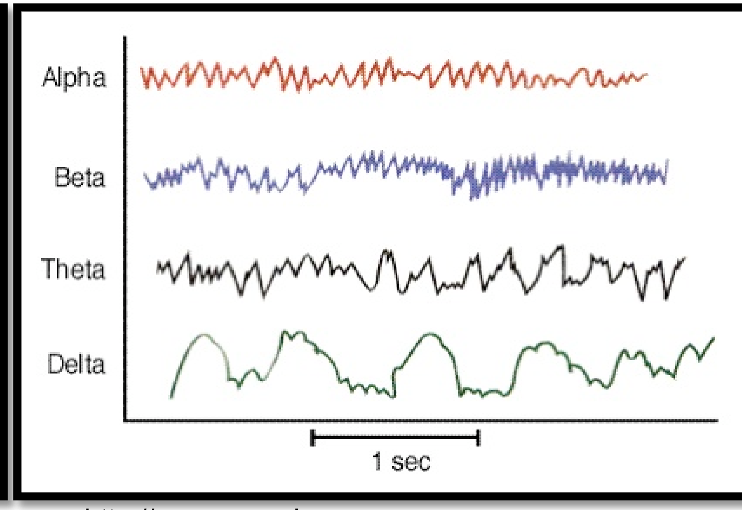
EEG STPR in NeuCube

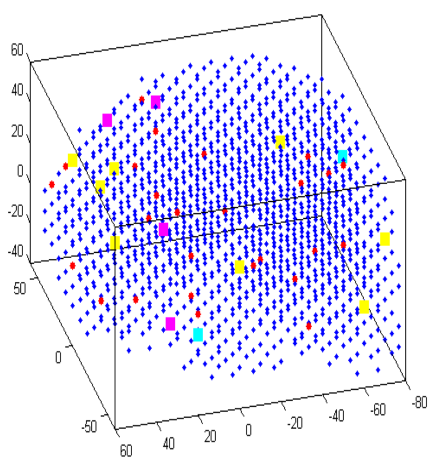


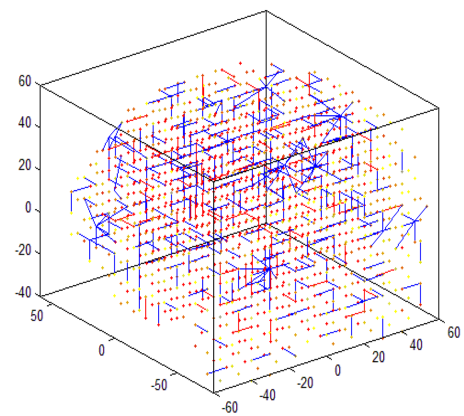


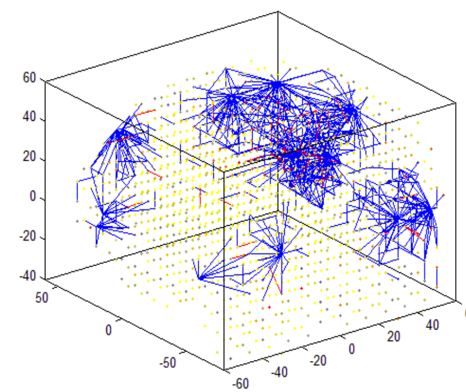


(McFarland, Anderson, MÜller, Schlögl, Krusienski , 2006)

http://www.nuroshop.com







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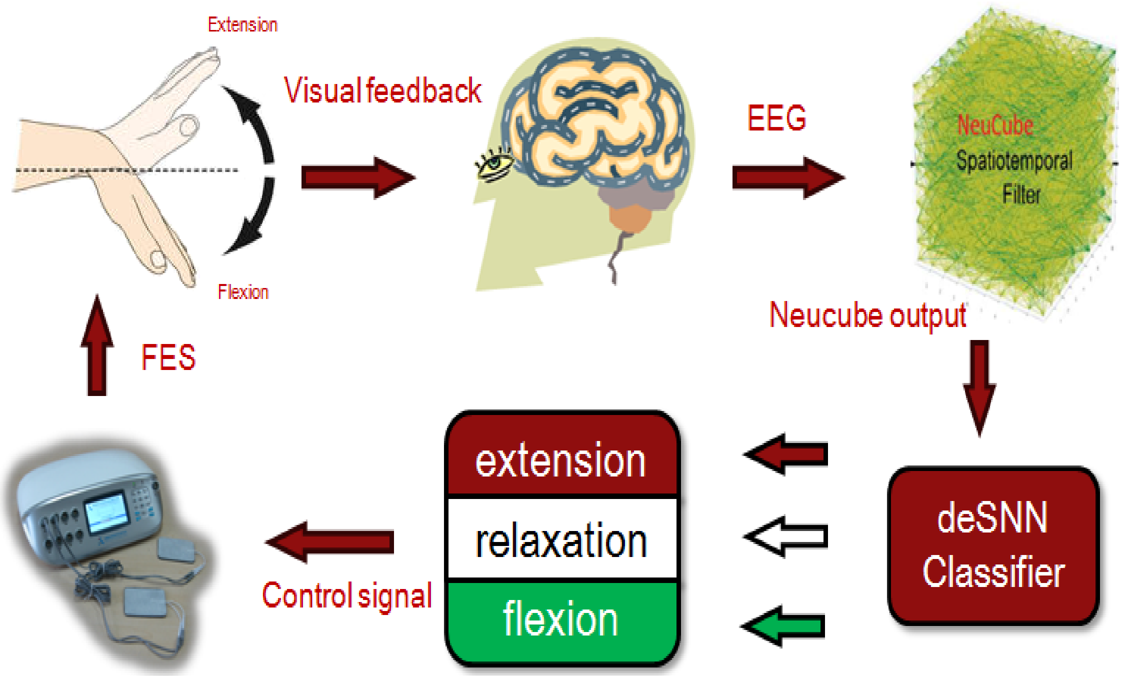
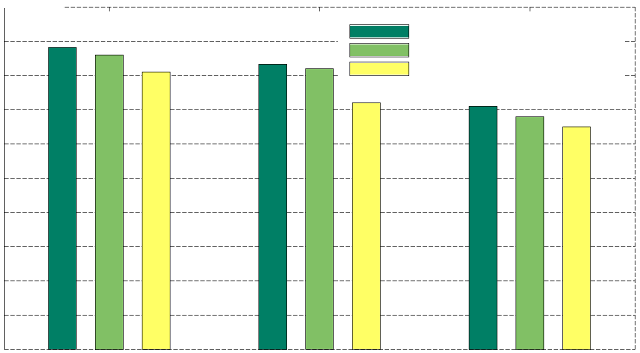
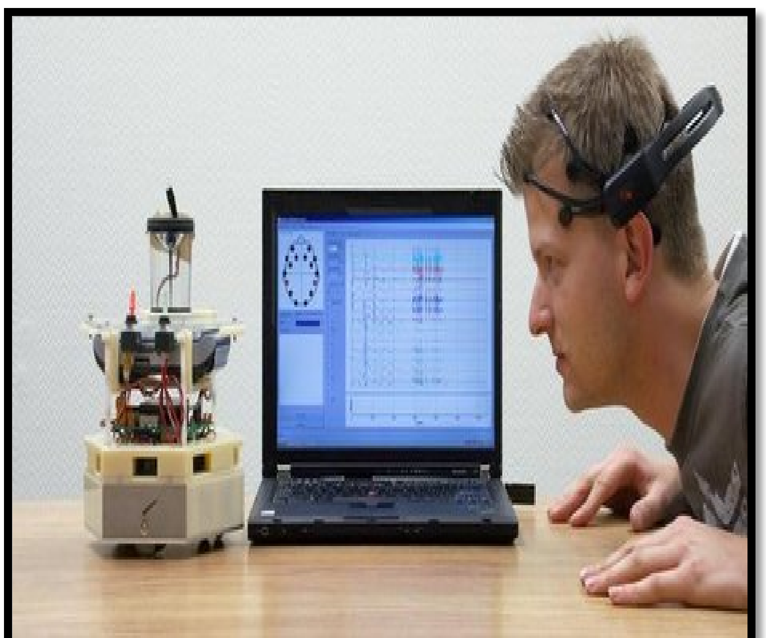
NeuCube for Neurorehabilitation





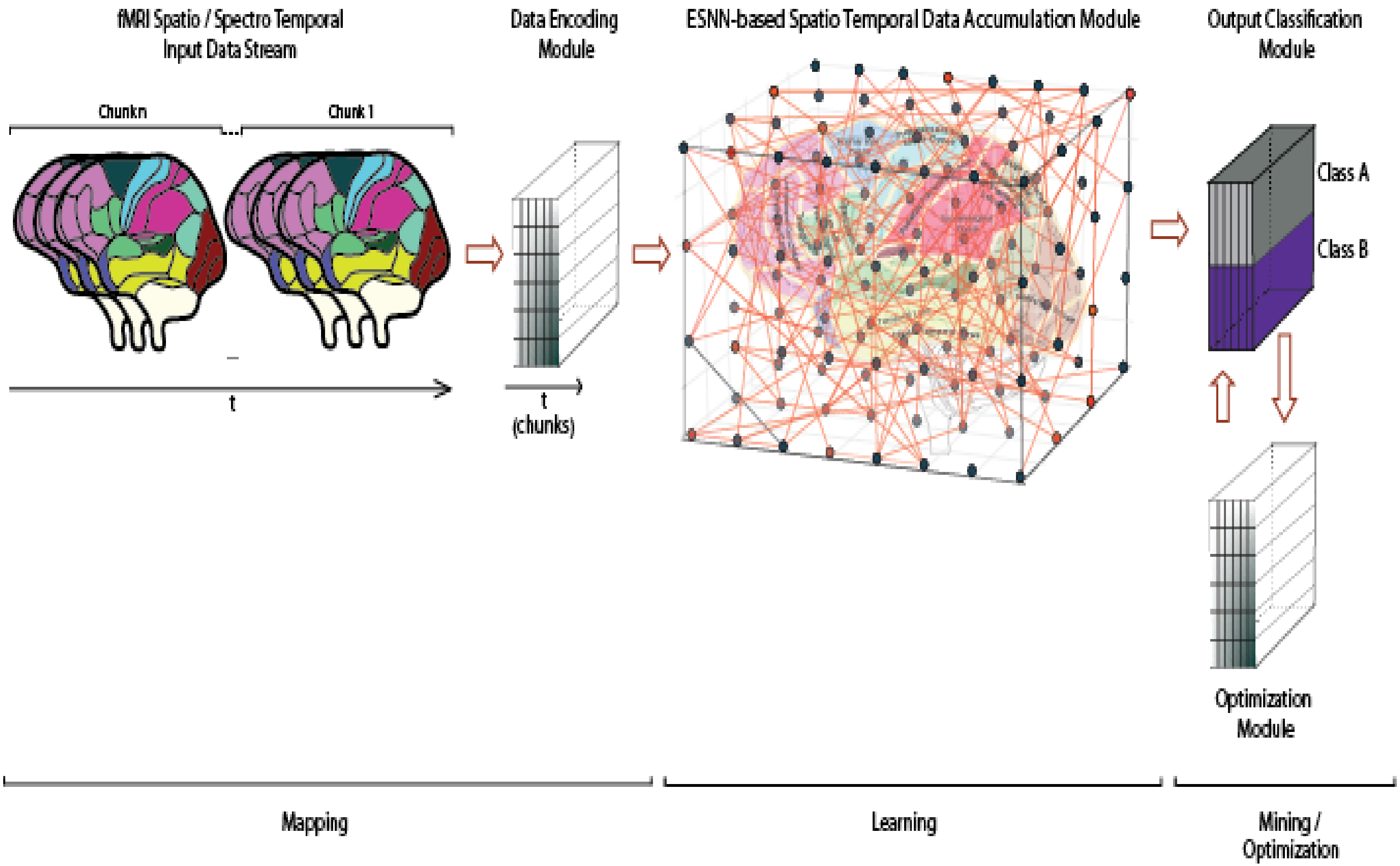
NeuCube for BCI

- 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, prof. Yamakawa (S.Schliebs)
- Neuro-rehabiltation and neuro-prosthetics (with CAS, Z-G Hou)
- Collaborative work with U.Aveiro (P.Georgieva)



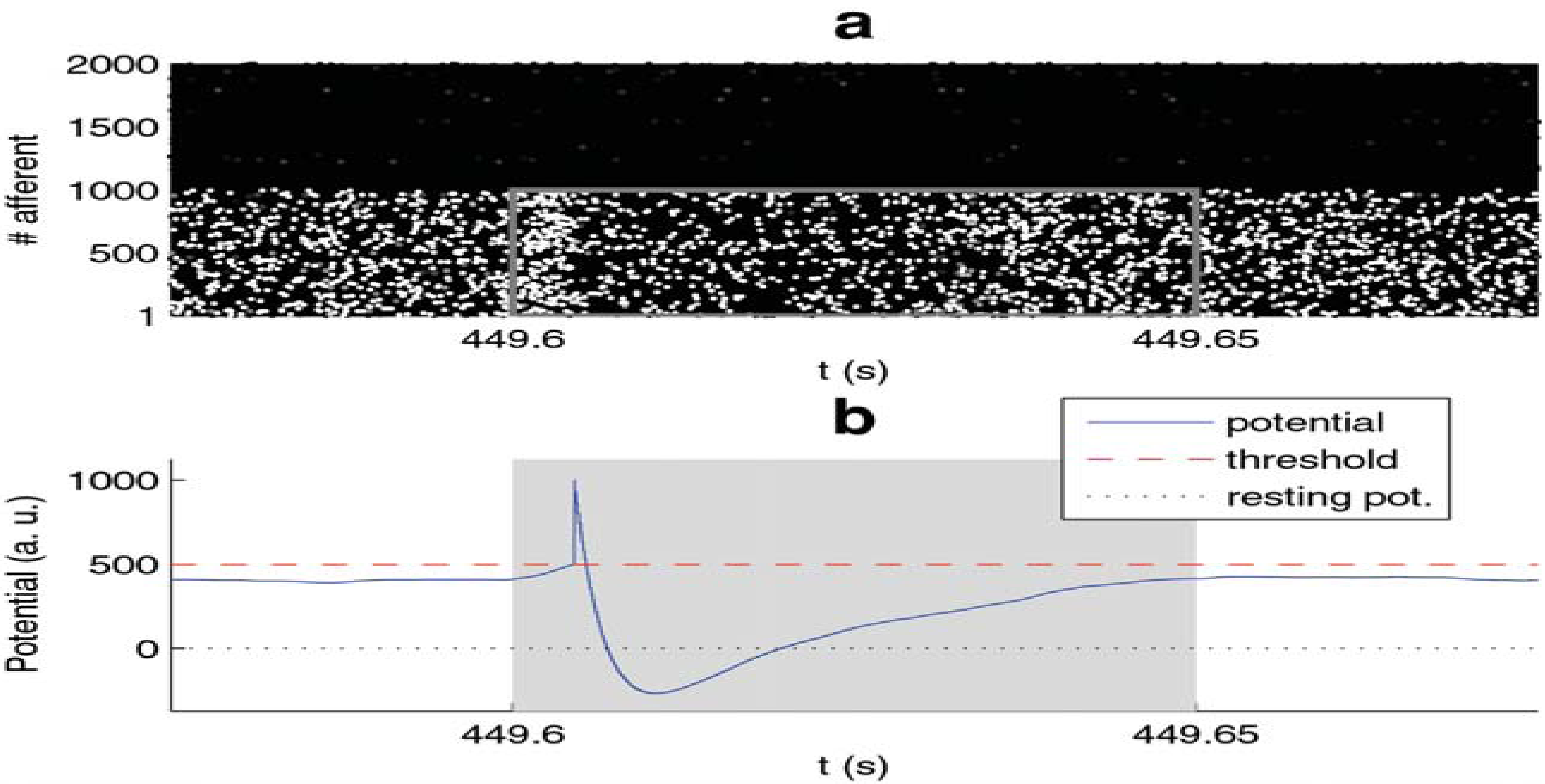
http://www.nzherald.co.nz

NeuCube for fMRI STBD

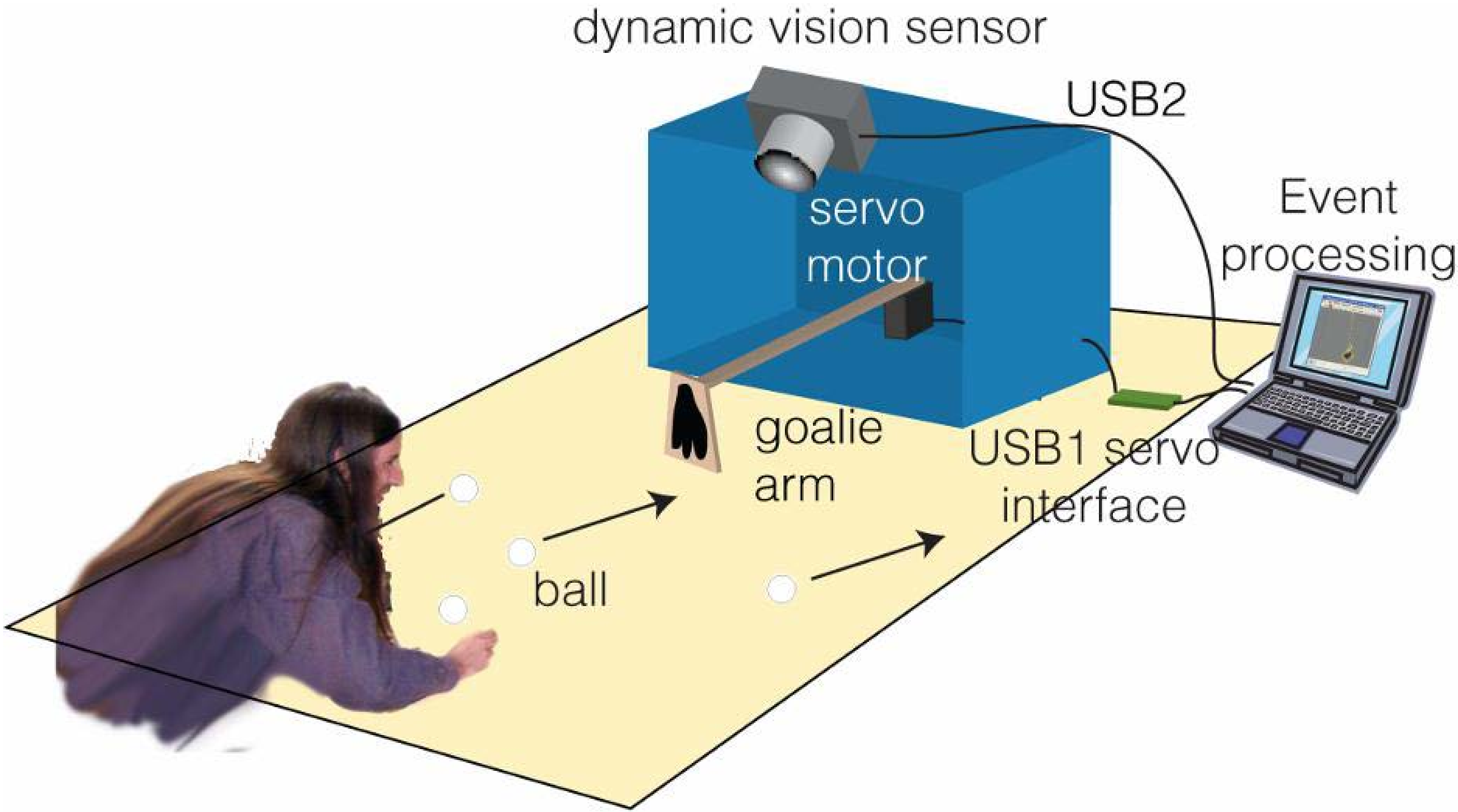


4. Early Detection of Events from Spatio-Temporal Data

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

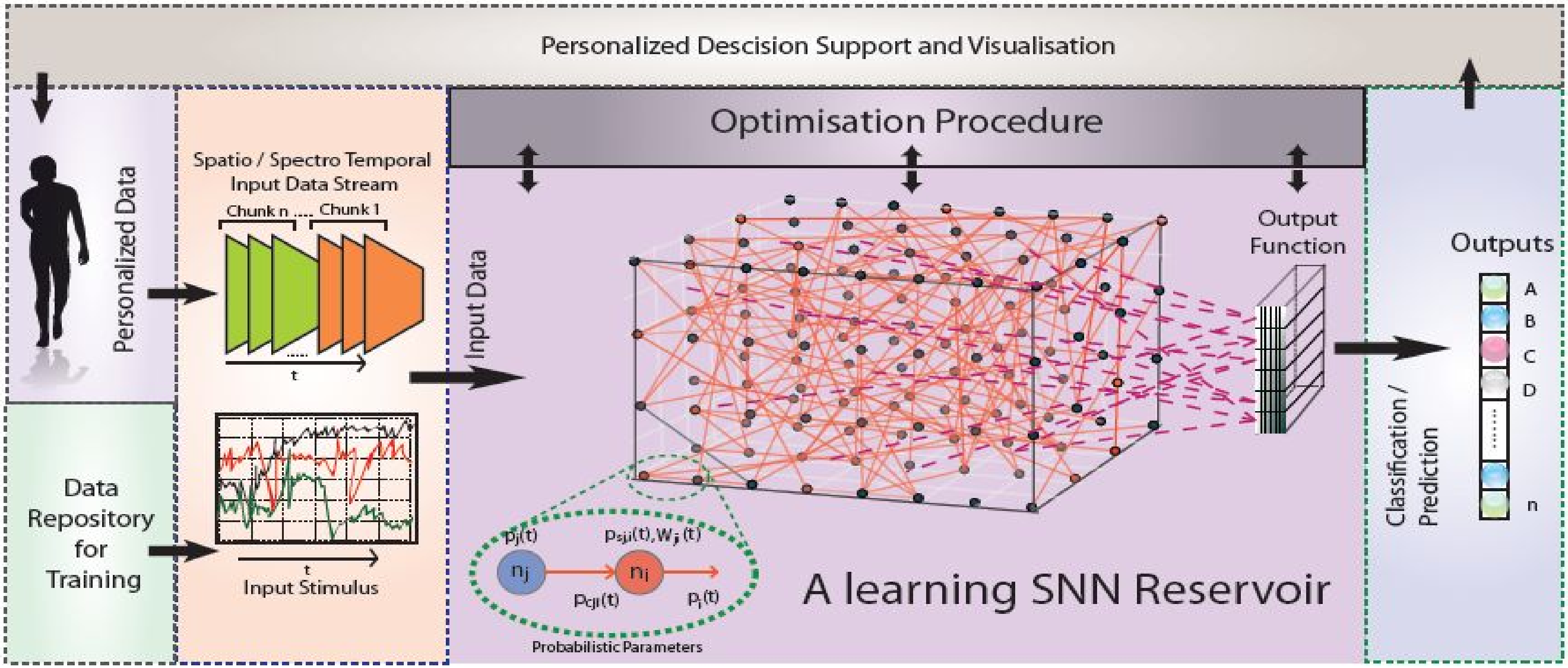


Early detection of a moving object with DVS
(T.Delbruck, INI, ETH. Zurich)



Personalised Predictive Systems

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

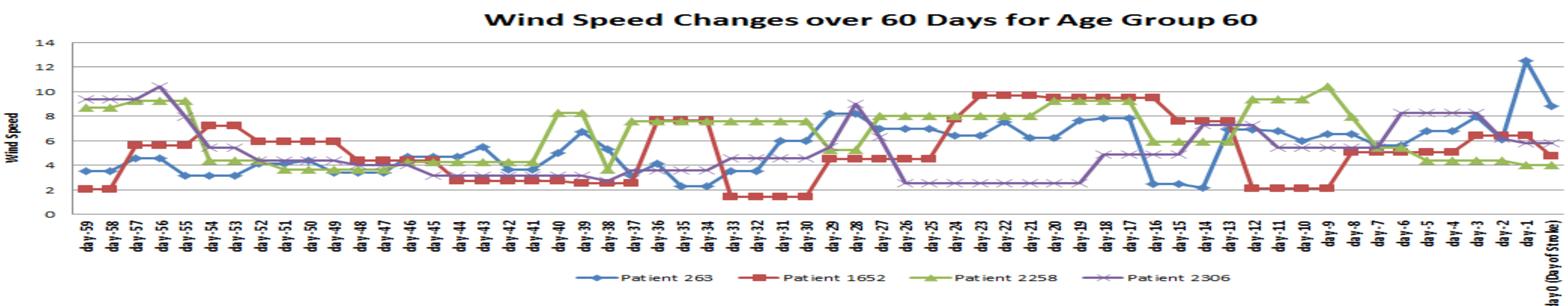


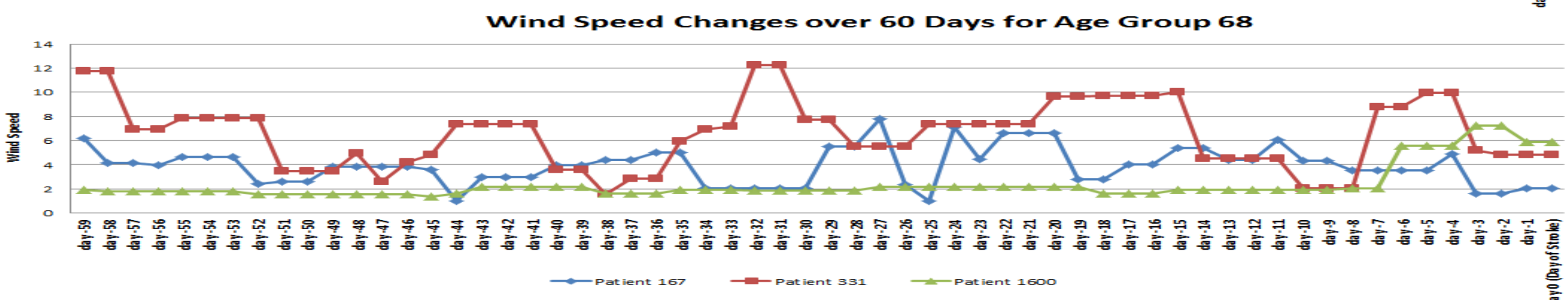
Personalised stroke occurrence prediction

The dataset consists of 11,453 samples (all with first occurrence of stroke).

Each sample is described by 9 features/variables:

- 4 static patient clinical features (age, gender, history of hypertension, smoking status, geographical region)
- 5 temporal weather variables: Temperature; Humidity; Atmospheric Pressure (kPA); Wind Speed (Knots) and Wind Chill (Degrees Celsius).
- All of these weather parameters were measured over a 60-day period preceding data of stroke (including the day of stroke occurrence as the last day).





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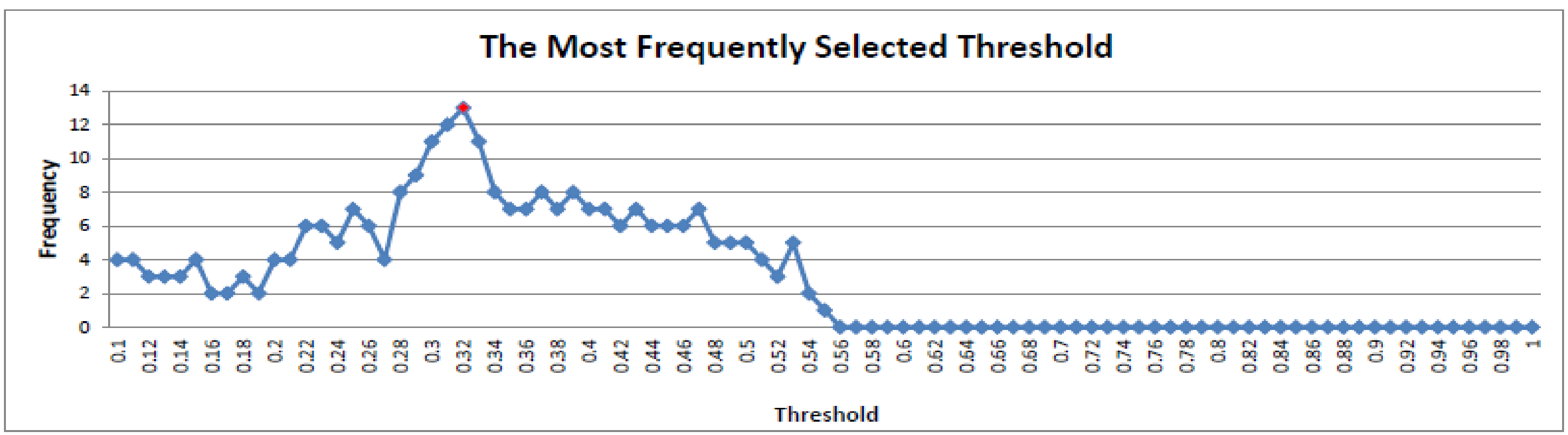
Results for personalised early stroke prediction

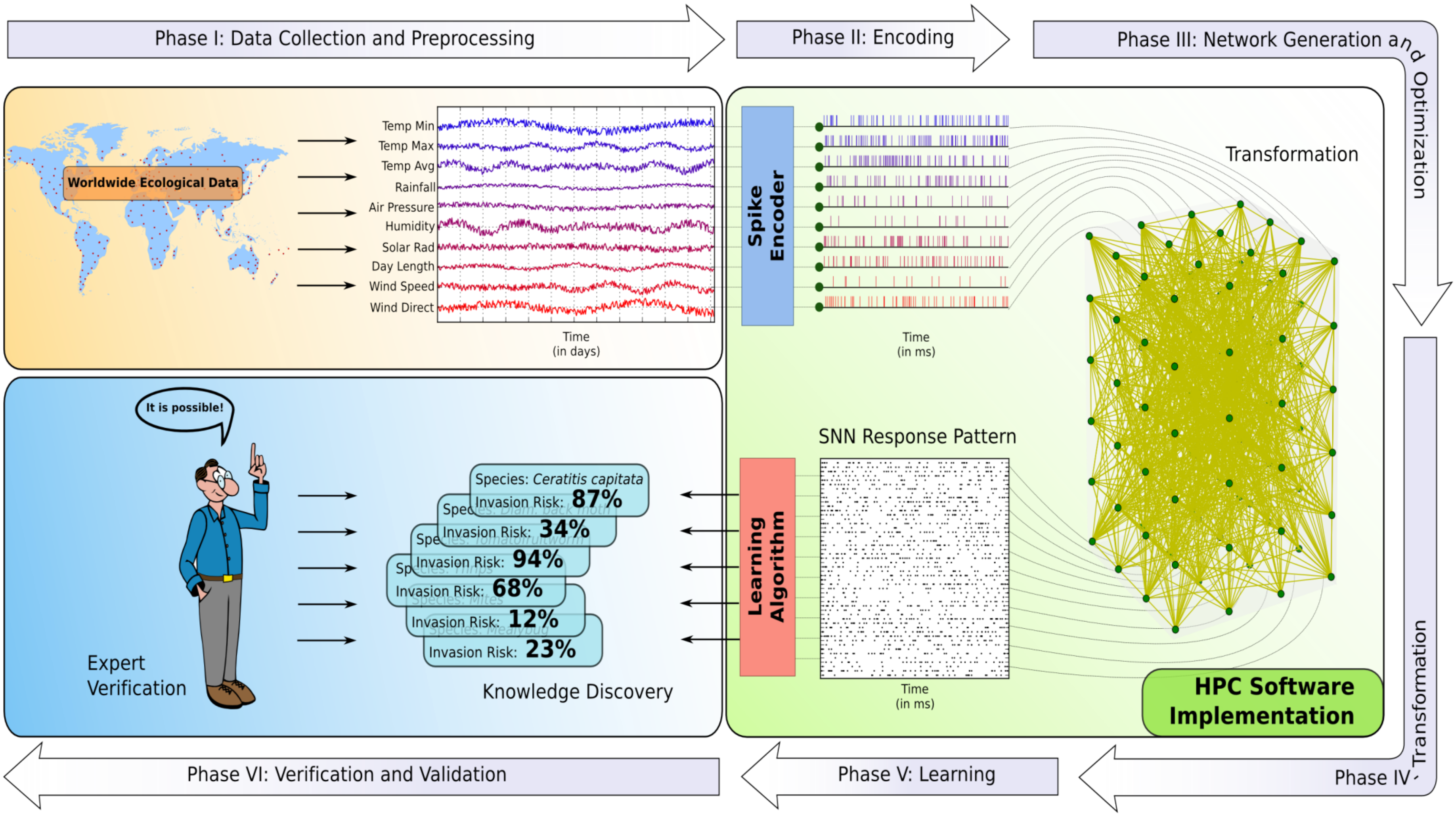
- SNN achieve better accuracy
- SNN predict stroke much earlier than other methods

Method	Overall accuracy (%)	TP – stroke prediction (%)	TN – no stroke (%)
Multiple Linear regression (MLR)	67.50	65	70
SVM	72.5	65	80
MLP	87.5	85	90
PMeSNNr	94	88	100

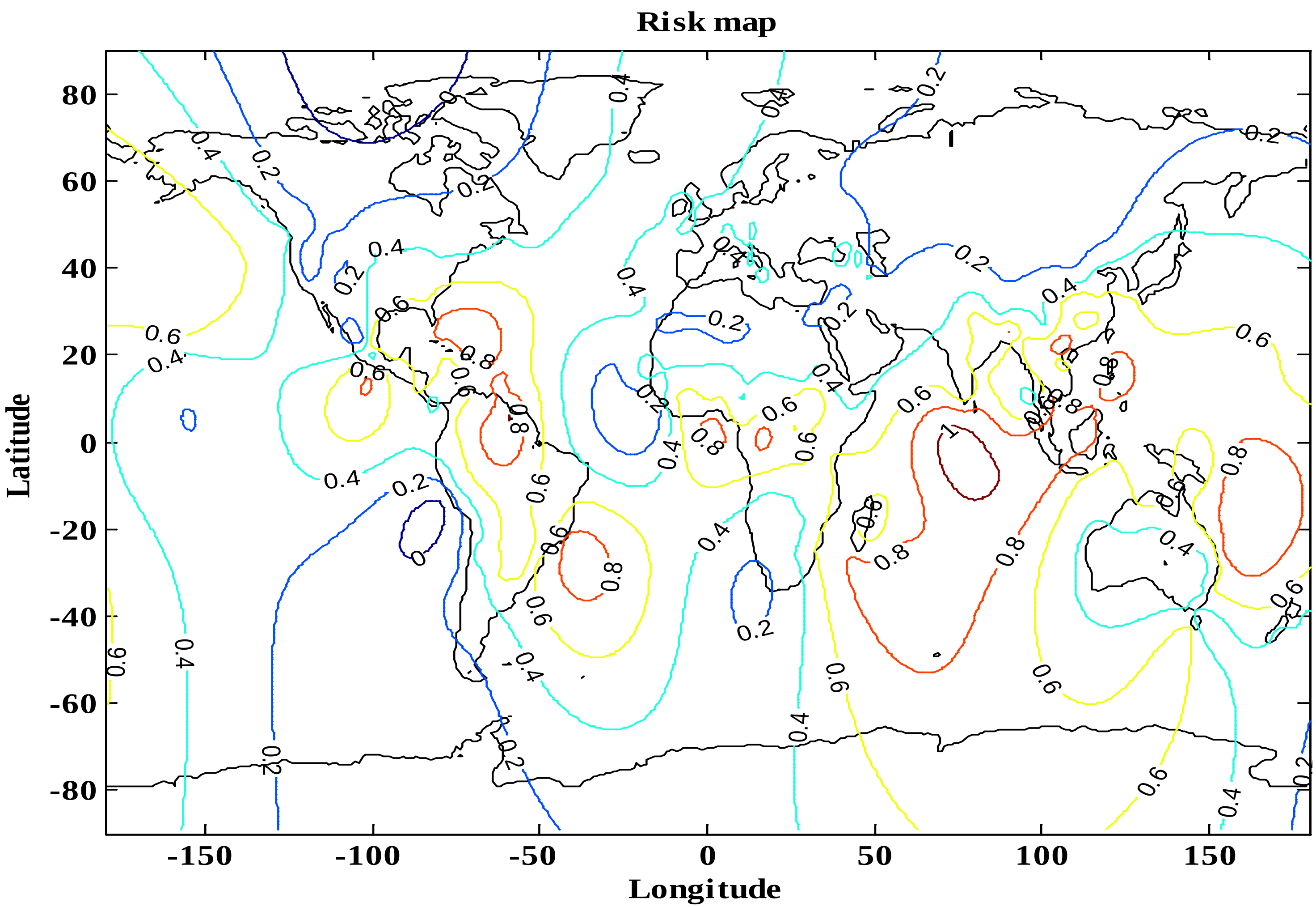


Early estimation of risk of establishment of invasive species on a certain *location* at a certain *time*

(S.Schliebs, Defoin-Platel, N.Kasabov, S.Worner et al, Neural Networks, No.22, 2009)



Example: Through modelling a world map was created for the estimation of the probability of *p.citri* insect establishment



5. Advantages and limitations of SNN

Advantages:

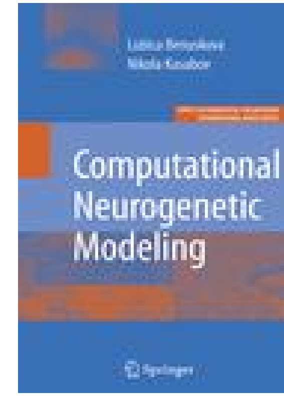
- Universal computational mechanism
- Extendable models, with more biologically related knowledge as it become available (e.g. genes, quantum information)
- Can learn spatio-temporal relationships from spatio-temporal data
- Fast and less computationally demanding (spikes are easy to compute)

Problems and limitations

- Sensitive to parameter values
- Large number of parameters that need to be optimised
- Unknown properties in terms of dealing with different types of spatio-temporal data
- No rigid theory yet

6. Future Directions

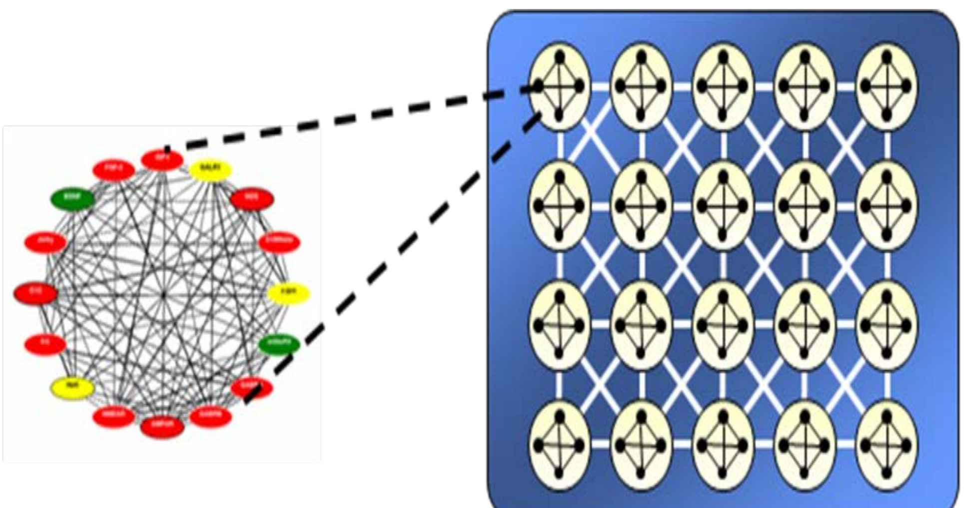
Computational Neuro-Genetic Modelling (CNGM)



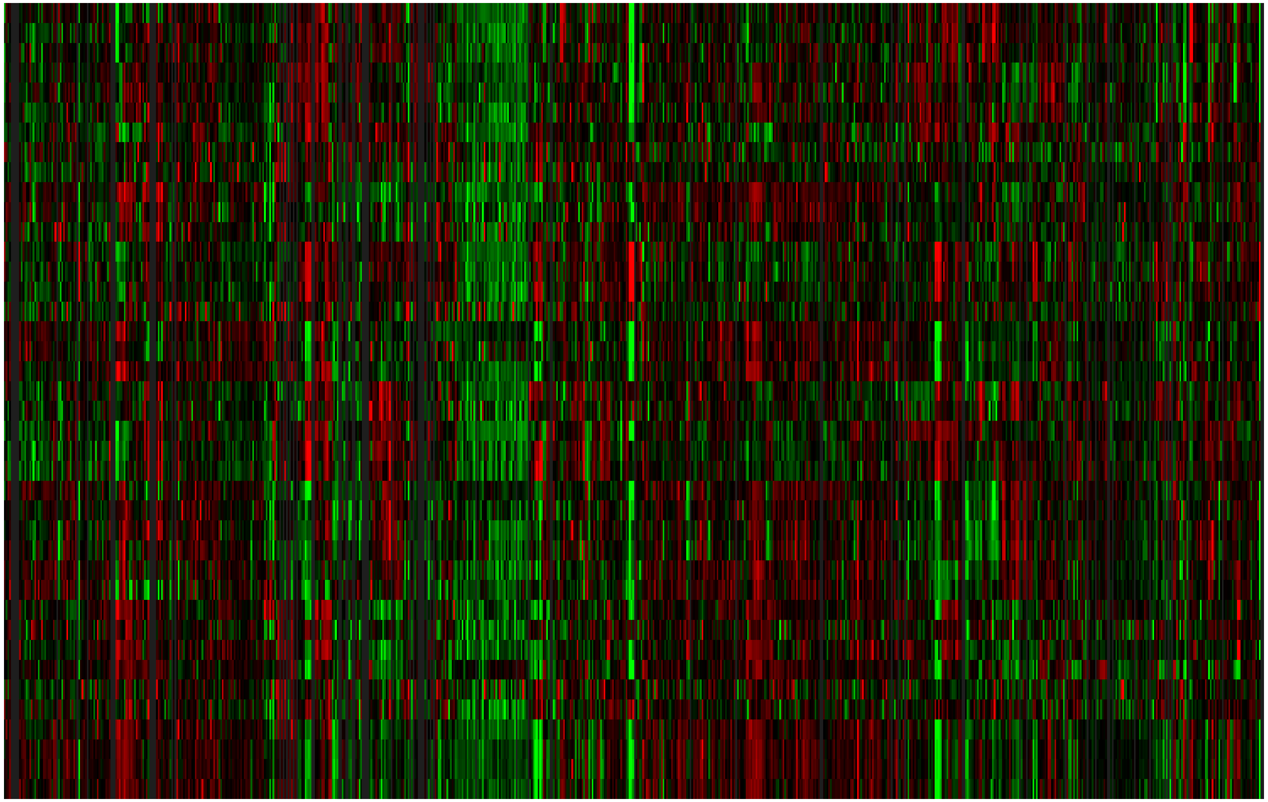
- Benuskova and Kasabov (2007)

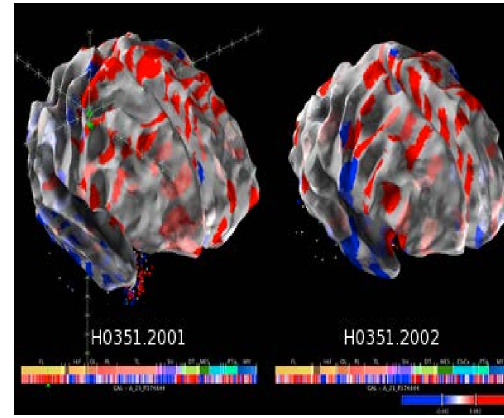
SNN that incorporate a gene regulatory network (GRN) as a dynamic paramter systems to capture dynamic interaction of genes (parameters) related to neuronal activities of the SNN.

- 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.
- Mark Sagar's emotional baby



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

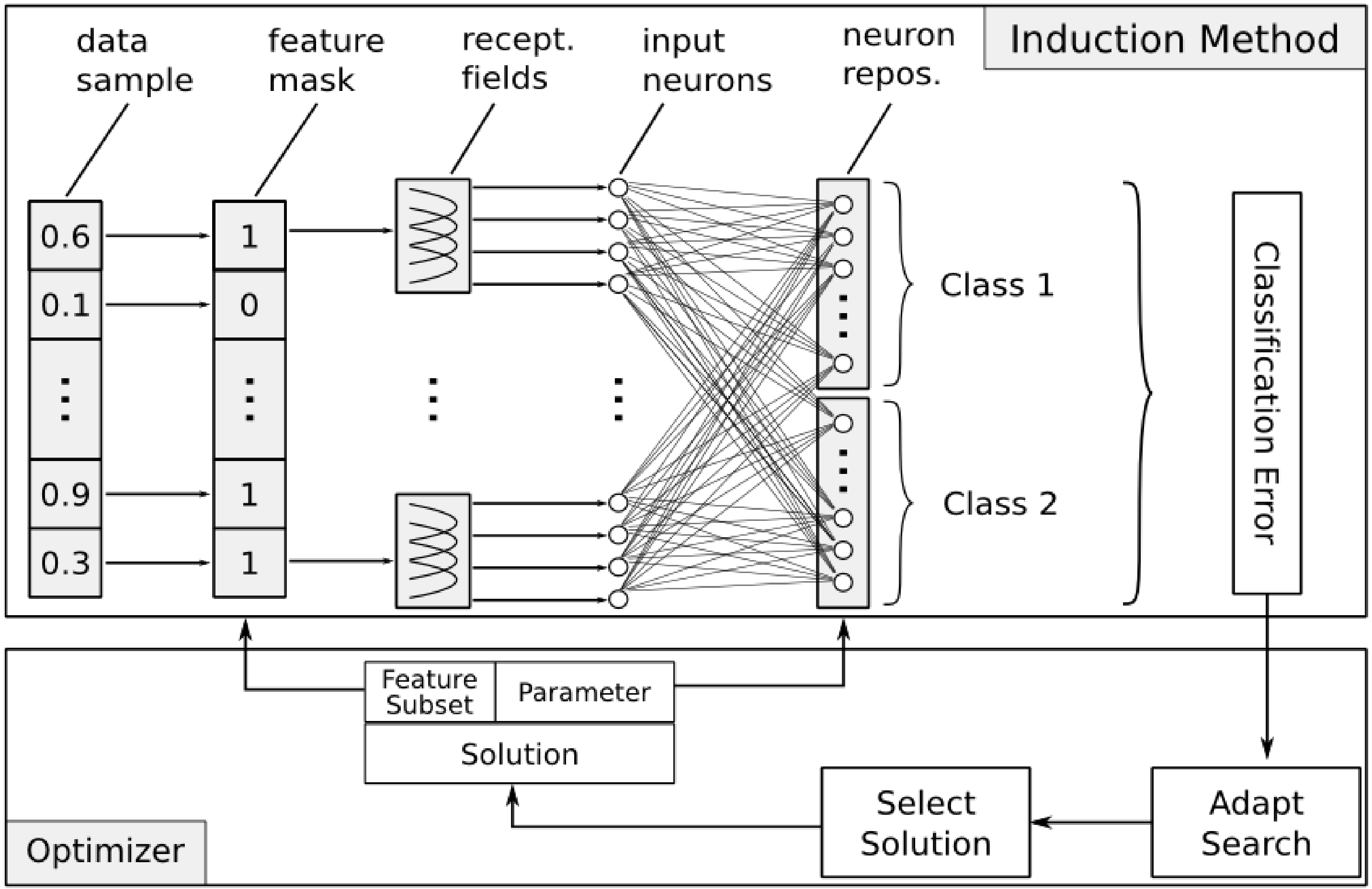




From the Brain Explorer: The Expression level of the genes (on the y-axis): ABAT A_23_P152505, ABAT A_24_P330684, ABAT CUST_52_PI416408490, ALDH5A1 A_24_P115007, ALDH5A1 A_24_P923353, ALDH5A1 A_24_P3761, AR A_23_P113111, AR CUST_16755_PI416261804, AR CUST_85_PI416408490, ARC A_23_P365738, ARC CUST_11672_PI416261804,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

Quantum-inspired EC for the optimisation of eSNN

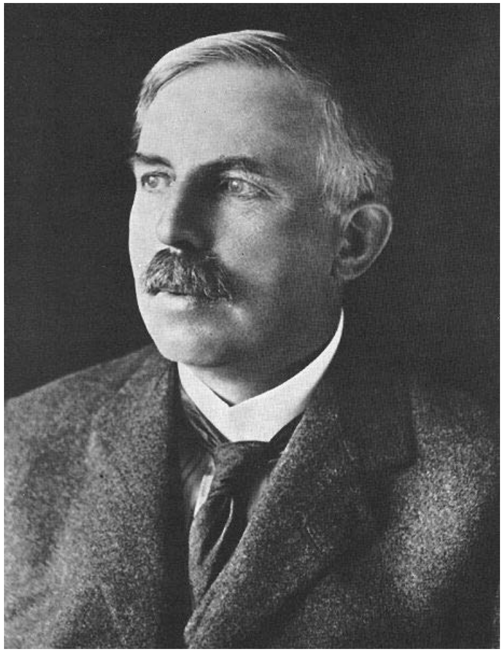
(Kasabov, 2007-2008; S.Schliebs, M.Defoin-Platel and N.Kasabov, 2008)



Quantum Inspired Technologies

- 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)

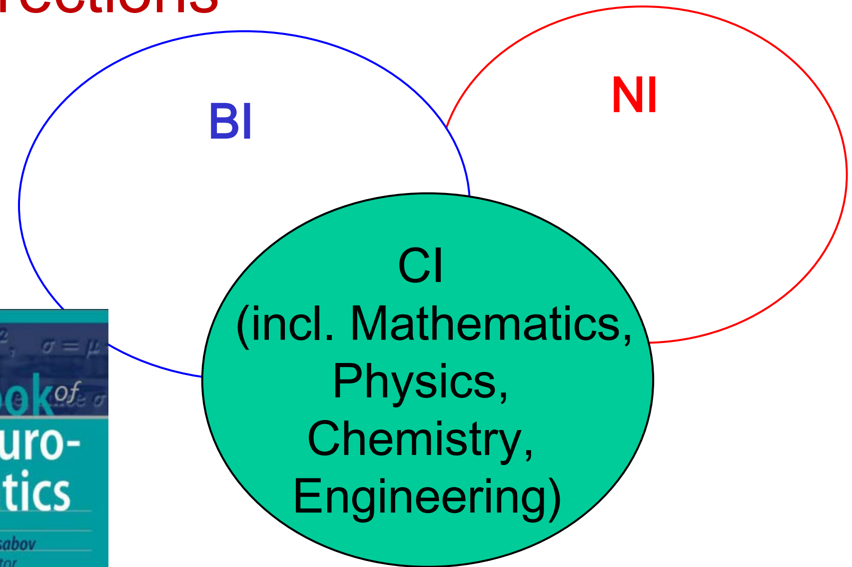
$$\begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m \end{bmatrix}$$

- Quantum gates

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

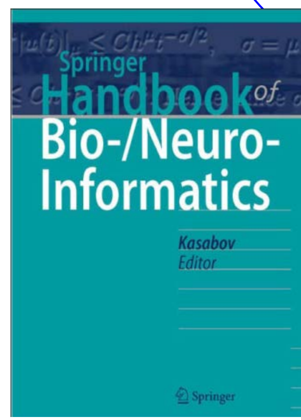
- Applications:
  - Specific algorithms with polynomial time complexity for NP-complete problems (e.g. factorising large numbers, Shor, 1997; cryptography)
  - Search algorithms (Grover, 1996), O($N^{1/2}$) vs O(N) complexity)
  - Quantum associative memories
  - Quantum inspired evolutionary algorithms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

…Future Directions

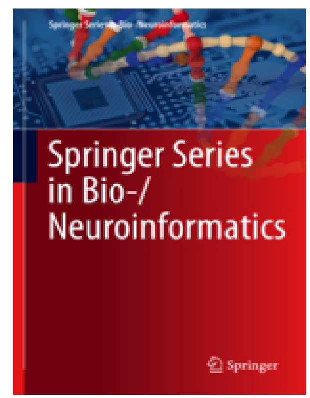


- Further interdisciplinary research in the three areas of CI, BI and NI

- The Springer Handbook of Bio-Neuroinformatics, 2013 (N.Kasabov, ed)

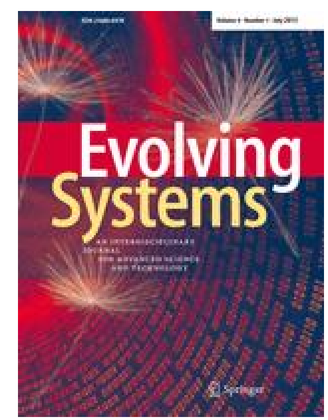


- The Springer Series in Bio-Neuroinformatics (N.Kasabov, ed)



- Springer journal *Evolving Systems*

  (ed. Angelov, Filev, Kasabov)



KEDRI: The Knowledge Engineering and Discovery Research Institute at AUT (www.kedri.aut.ac.nz)

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