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Connectivity, Computability and Complexity of Evolving Spiking Neural Networks and Applications for Computational Intelligence

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Abstract

SNN have a tremendous potential as a new paradigm to implement and achieve computational intelligence (CI).

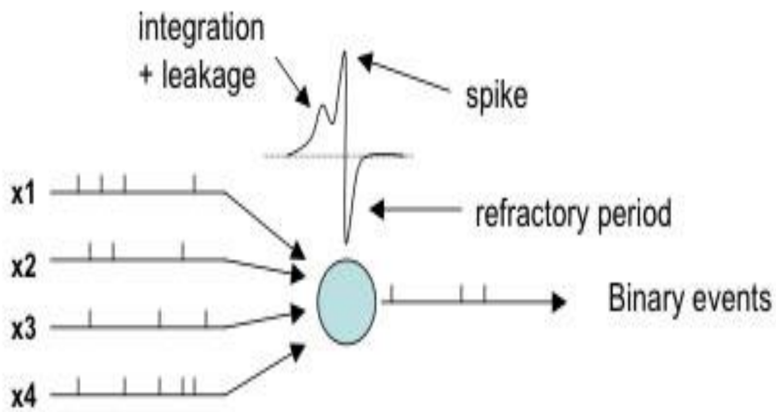
Current models have some limitations that prevent their wider application.

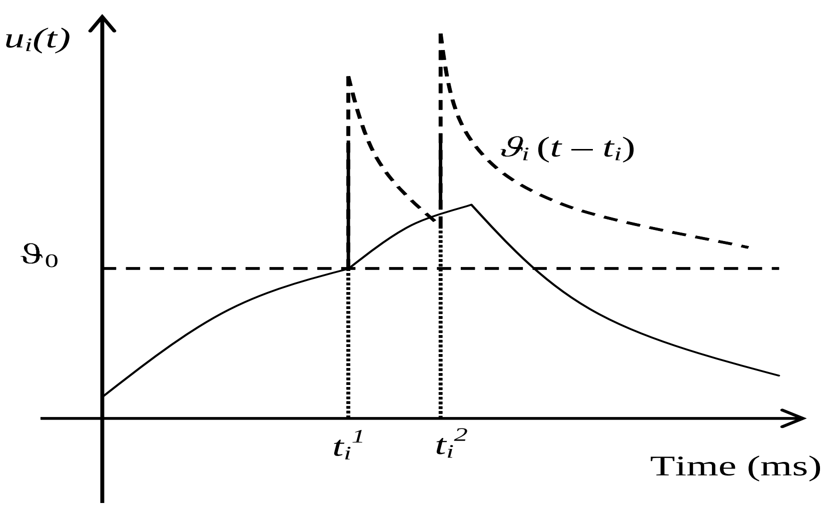
Based on biological evidence, new SNN models can be developed to solve complex generic and specific tasks of CI, where *connectivity, computability and complexity* need to be optimised.

Content

1) SNN: Models, applications, challenges.
2) Simple evolving SNN (seSNN).
3) Probabilistic evolving SNN (peSNN).
4) Probabilistic quantum inspired evolving SNN (pqeSNN).
5) Neuro-genetic evolving SNN (ngeSNN).
6) Further SNN models and applications.

1. SNN: Models, Applications, Challenges





Information processing principles in neurons and neural networks:

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

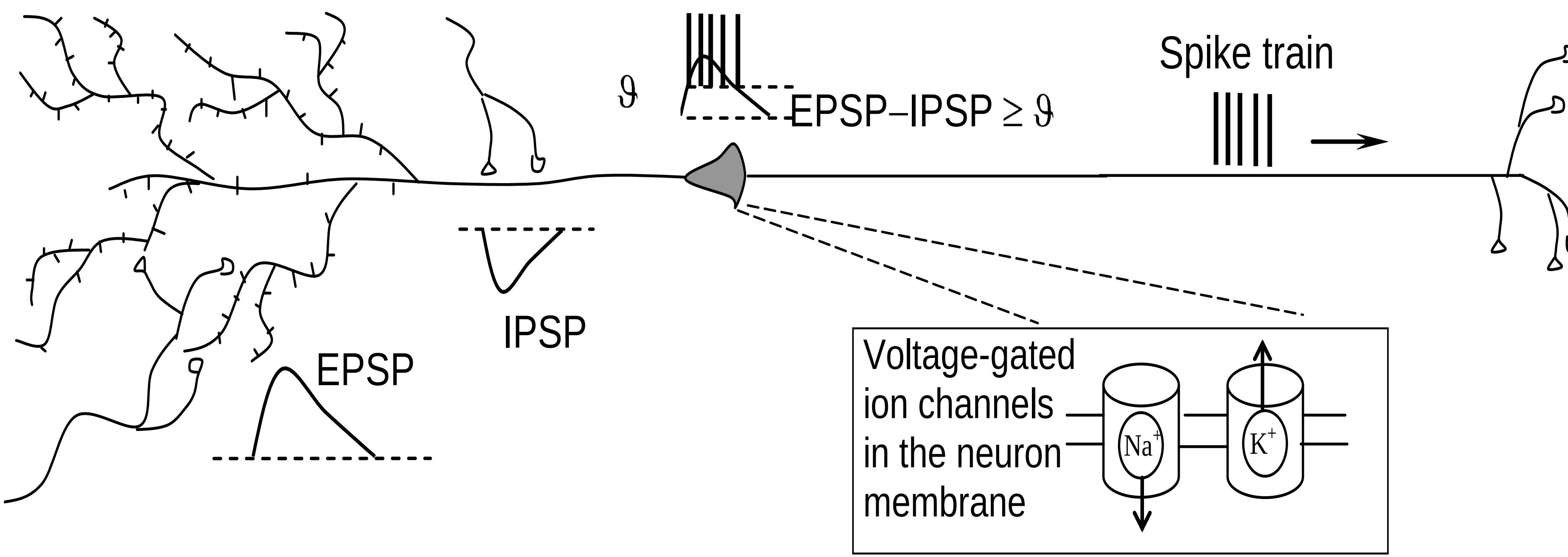
They offer the potential for:

- Modelling cognitive functions through patterns of neuronal spiking activity;
- Integration of different 'levels 'of information processing, i.e.: modelling neuronal activities based on genes and proteins.

Rich neurophysiological information about the spiking activities in the brain is already available

(Singer, Abeles, Freeman, Villa, Kojima, Yamaguchi, Gat, Hopfield, Izhikevich, Reece, Thorpe, Fize, & Marlot, Villa, Tetko, Hyland, & Najem, ...)

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.



Many questions have to be answered before artificial SNN are applied for a **generic** or a **specific** task:

- What model of an artificial neuron to use?
- How to **connect** the neurons in a SNN?
- How to encode information in the SNN?
- What learning rule to apply?
- What this SNN can **compute** efficiently and what it cannot compute?
- What is the time- and space- **complexity** of the SNN solution?
- What CI techniques can be applied to enhance the solution (e.g. optimisation through evolutionary algorithms (EA))?
- What software and hardware support will be needed?

- The main question always remains:

TO SPIKE OR NOT TO SPIKE?

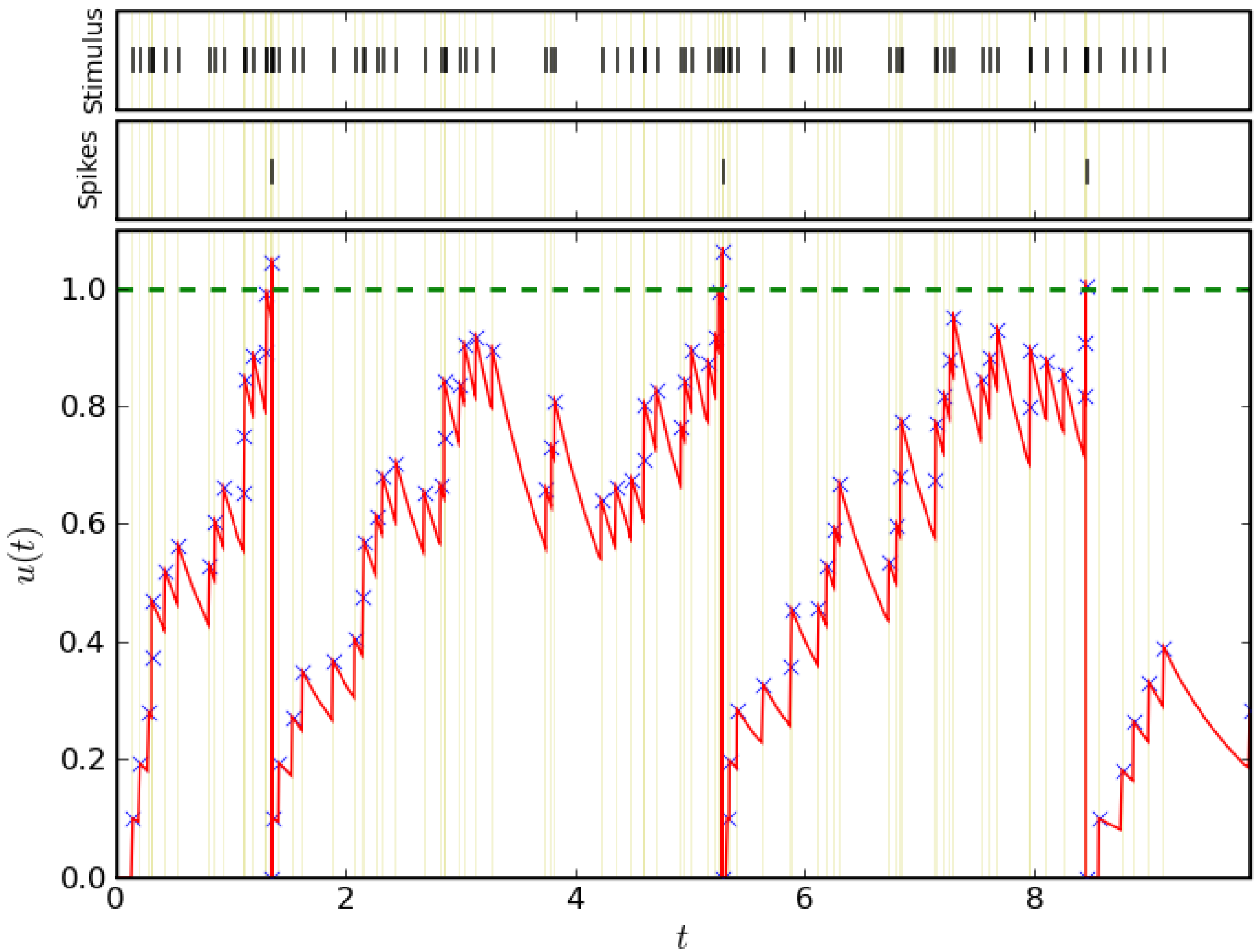
Some models of Spiking Neurons

- **'Microscopic Level':** Modeling of ion channels, that depend on presence/absence of various chemical messenger molecules:
  - Hodgkin-Huxley's (1952);
  - Izhikevich's (2003);
  - Many variants of the above (e.g. FitzHugh-Nagumo model);
  - Specialised neuronal models, e.g. Inferior Colliculus (ICX) (INI, PNAS, 2010)

- **'Macroscopic Level':** Neuron is a homogenous unit, receiving and emitting spikes according to defined internal dynamics (Maass; Gerstner,Kistler):
  - Spike response model (SRM);
  - Integrate-and-Fire models (IF, LIF);
  - *Adaptive exponential IFM* (Brette and Gerstner, 2005)

- **'Integrative':**
  - A probabilistic spiking neuron model (pSNM)
  - A neuro-genetic SNM (ngSNM)

Dynamics of the LIF neuron



Neural Information Encoding

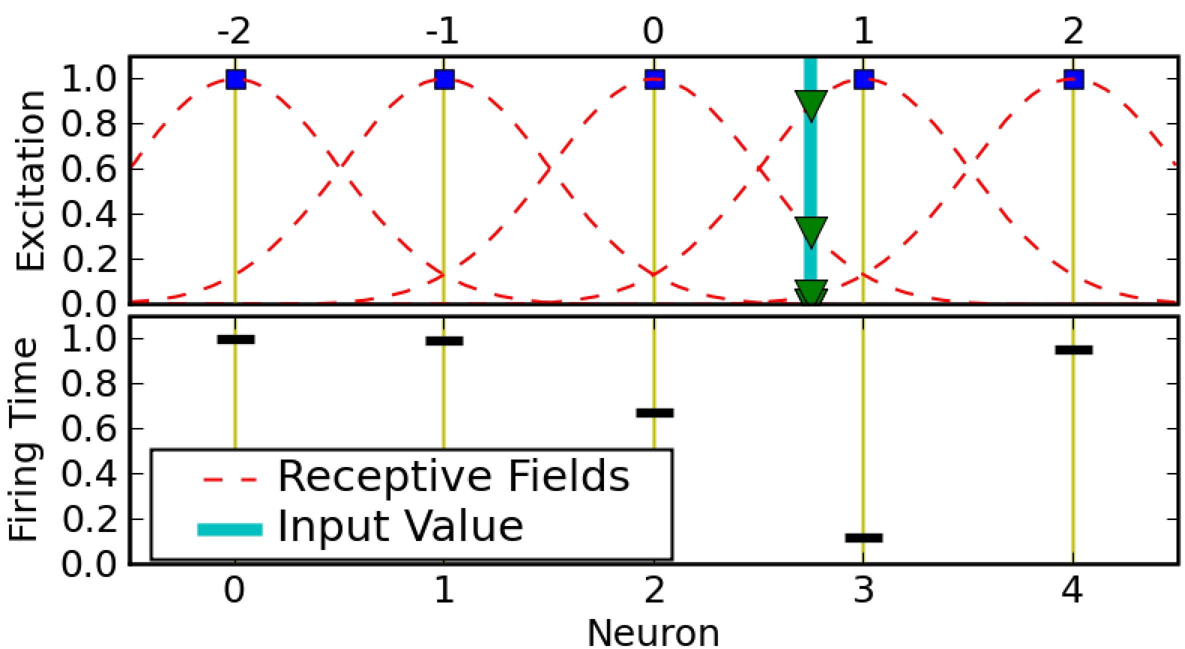
- Fundamental questions in SNN:
  - What is the input- and the output information encoding?
  - What is the internal code used by neurons to transmit information?
  - Memory encoding;
  - Instructive coding;
  - Can we read and understand the message of the neural activity?

- Traditionally two main theories of neural encoding:
  - Rate Codes: Average of many spike events (mean firing rate of a neuron) carries most, if not all, of the information;
  - Pulse or Spike Codes: Exact spike time carries information.

- Spike-based sensory systems for information encoding into spikes, e.g.:
  - Visual information, retina chip (Tobias Delbruk, INI);
  - Acoustic, cochlea chip (Shin-Chii Liu, INI).

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



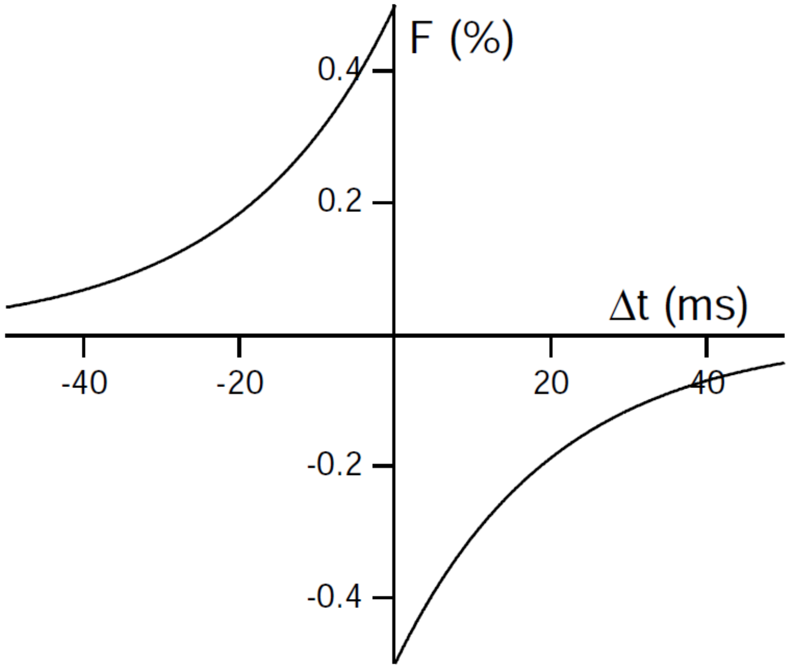
Learning in SNN

- BCM (Bienenstock, Cooper and Munro's);
- Hebbian learning;
- Spike-timing dependent plasticity (STDP);
- Time-to-first-spike principle (used by Thorpe);
- Stochastic spike-driven synaptic plasticity (membrane potential based STDP) (Brader, Senn and Fusi, 2007)
- Perceptron learning (learn when misclassify) (D'Souza, SCLiu, Hahnloser, INI);
- Reinforcement learning;
- SpikeProp – supervised error back-propagation, similar to learning in classical MLP;
- (Linear) readout functions for the Liquid State Machines (Maas et al);
- ReSuMe – Remote Supervised Method;
- Weight optimization based on evolutionary algorithms (EA);
- ...other learning rules....

Spike-Time Dependent Plasticity (STDP)

- 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 post-synaptic action potentials

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



Thorpe's Model utilising time-to-first-spike principle

- Simple but computationally efficient neural model, in which early spikes are stronger weighted
- Model was inspired by the neural processing of the human eye and introduced by S. Thorpe et. al. 1997
- PSP $u_i(t)$ of a neuron i:

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

- w_{ji} is the weight of the connection between neuron j and i, $f(j)$ is the firing time of j, m_i a parameter of the model (***modulation factor***)
- Function *order* (j) represents the rank of the spike emitted by neuron j and receive at neuron i

Some SNN software and hardware platforms

- Software simulators:
    - Neuron
    - Genesis
    - Izhikevich software
    - eSNN and CNGM (www.kedri.info)
    - SpikeNet (Delorme and Thorpe)
    - jAER (INI, T. Delbruck)

- Hardware realisations:
    - SPINN (TU Berlin)
    - SpinNNaker (U.Manchester)
    - FPGA (U.Ulster, McGinnity)
    - BlueGene (IBM, Almaden, Modha)
    - Neuromorphic AER circuits and systems (G.Indivieri, INI, Zurich)

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Some SNN applications for CI

- Modeling brain synapses (EPFL Lausanne, Markram);
- Large scale brain modeling (UCSD, Izhikevich).
- Engineering applications (IBM-Modha; Ulster- McGinnity,)
- Real-time pattern classification (Bothe et al)
- Robotics (R.Duro)
- Image processing and face recognition (Thorpe et al)
- Speech and sound modeling (Villa)
- Adaptive multimodal audio-visual information processing (KEDRI)

Problems and challenges with SNN models

- Most spiking neuron models are too simplistic;
- Most SNN models have a fixed structure and functionality and do not evolve incrementally from incoming data;
- Most SNN models are deterministic and it could be difficult to model complex stochastic processes;
- There are very few SNN models that allow the integration of genetic and spiking activity information;
- An integrated study and optimisation of **connectivity, computability and complexity** of SNN is needed for each application;

The challenge is to develop new SNN models that would address the above problems, e.g.:

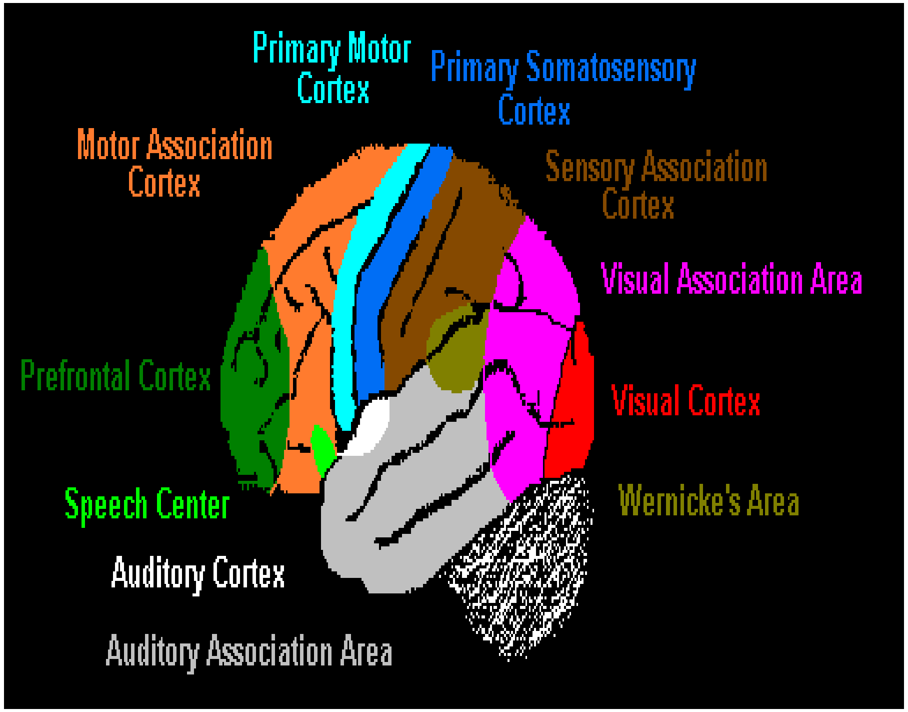
- seSNN (section 2)
- peSNN (section3)
- pqeSNN (section 4)
- ngeSNN (section 5)

Problems and challenges with SNN applications

Generic application problems, that are still difficult to achieve with traditional SNN and some of them addressed here are:

- Incremental learning for pattern recognition;
- Learning complex spatio-temporal patterns (acoustic-, visual-, audio-visual-, EEG-, fMRI and other brain data);
- Knowledge extraction (e.g. association rules);
- Feature selection;
- Learning finite automata of large number of states;
- Building associative memories with a very large capacity;
- Computational neuro-genetic modelling (CNGM).

2. Simple evolving SNN (seSNN)



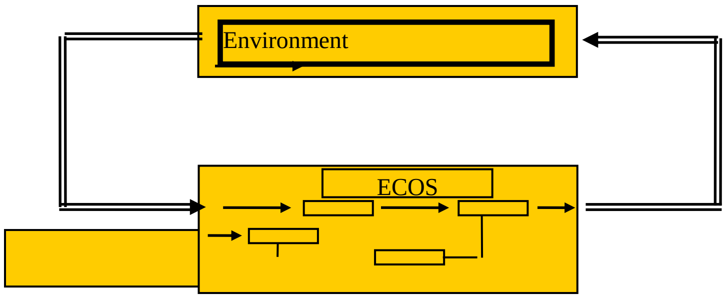
Inspiration from the brain

- The brain evolves through genetic “pre-wiring” and life-long learning
- Evolving structures and functions
- Evolving features
- Evolving knowledge
- Local (e.g. cluster-based) learning and global optimisation
- Memory (prototype)-based learning, “traceable”
- Multimodal, incremental learning
- Spiking activity
- Genes/proteins involved
- Quantum effects in ion channels

The challenge: To develop evolving SNN models (eSNN) to facilitate the creation of evolving CI.

Principles 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.



- Early ECOS models: RAN (J.Platt, 1991) – evolving RBF NN; RAN with a long term memory – Abe et al, ; Incremental FuzzyARTMAP (Carpenter , Grossberg); Growing gas; EFuNN (Kasabov, 1998, 2001); ESOM (Deng and Kasabov, 2002); DENFIS (Kasabov and Song, 2002); EFuRS, eTS (P.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, A. Koenig2005-); Incremental feature selection (Ozawa, Pang et al).

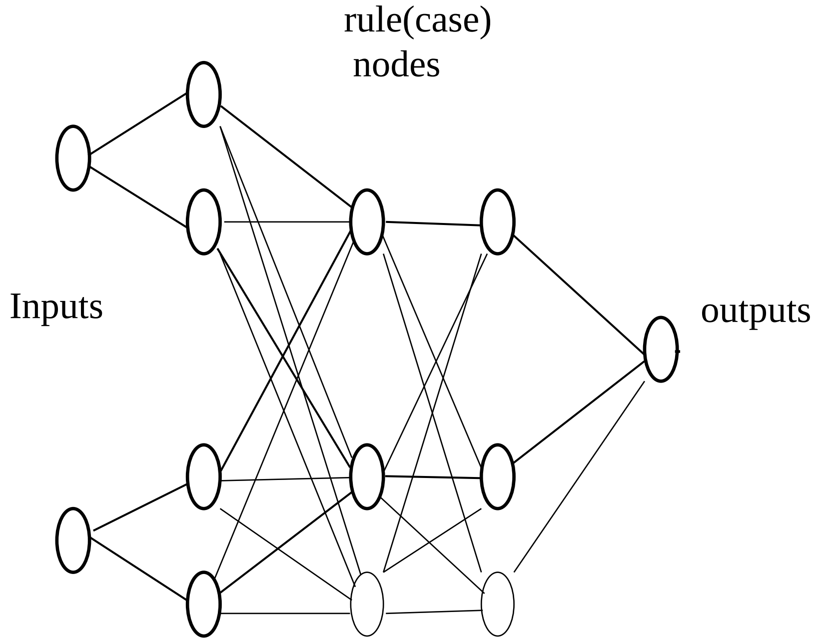
Example: Evolving Fuzzy Neural Networks (EFuNN) for incremental supervised learning

- As a general case, input and/or output variables can be non-fuzzy (crisp) or fuzzy.
- EFuNN, N. Kasabov, IEEE Tr SMC, 2001.
- Incremental, supervised clustering.
- New neurons are created and connection weights are changed based on *Euclidean distance* between input vectors and prototype nodes:

  Δ**w_i**=lrate * D(**x**, N),

  and on the output error:

  Δ**w_o**=lrate * E(y, O)



A seSNN model

(Kasabov, 2007; Wysoski, Benuskova and Kasabov, 2006-2009)

- Creating and merging neurons based on localised information
- 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 > *SIMthreshold* THEN Merge newly created neuron with the most similar neuron, where N is the number of samples previously used to update the respective neuron.

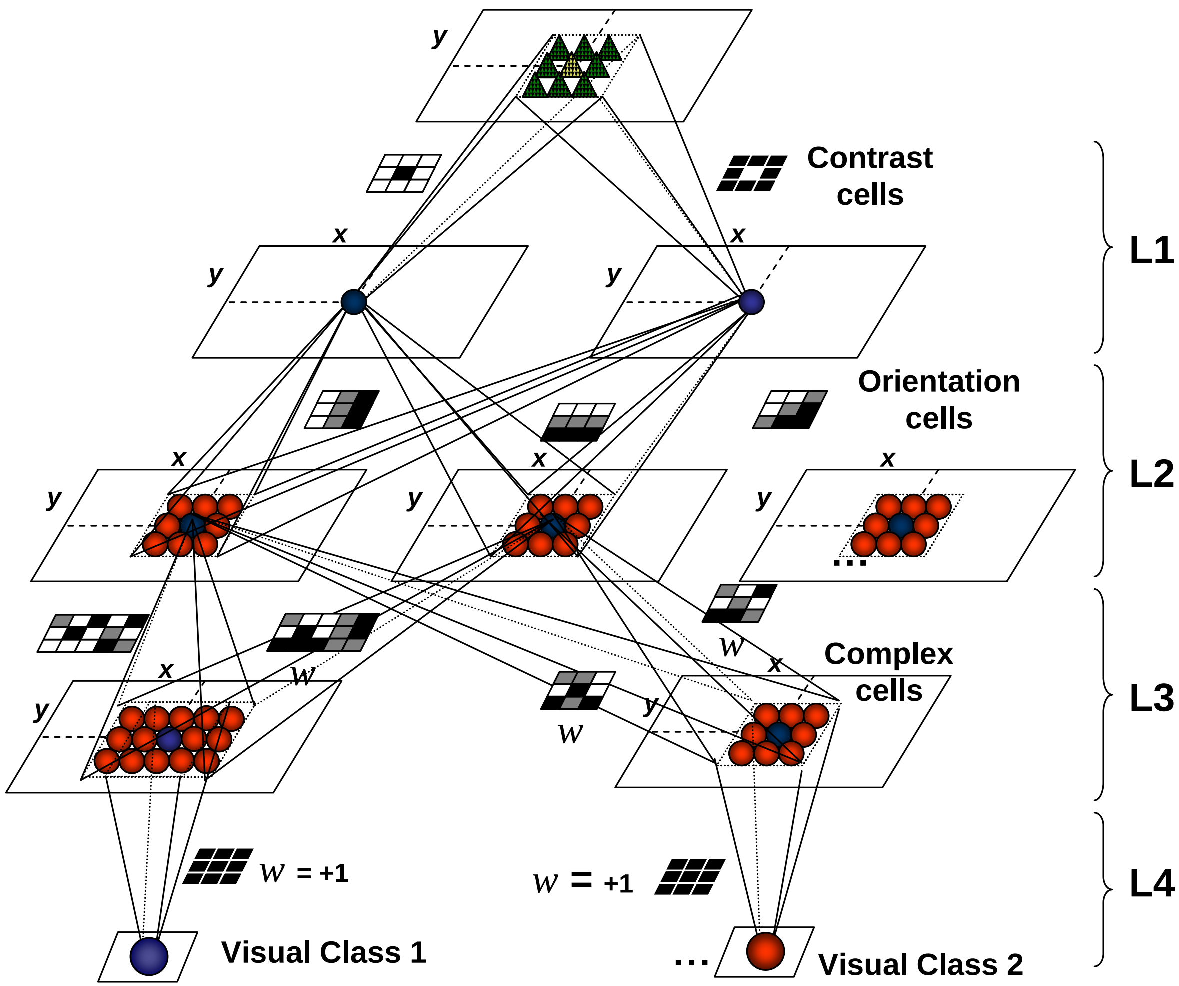
d) Update the corresponding PSP threshold ϑ:

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

- Three main parameters of the eSNN: Modulation factor *m*; Spiking threshold ϑ; *SIM*threshold

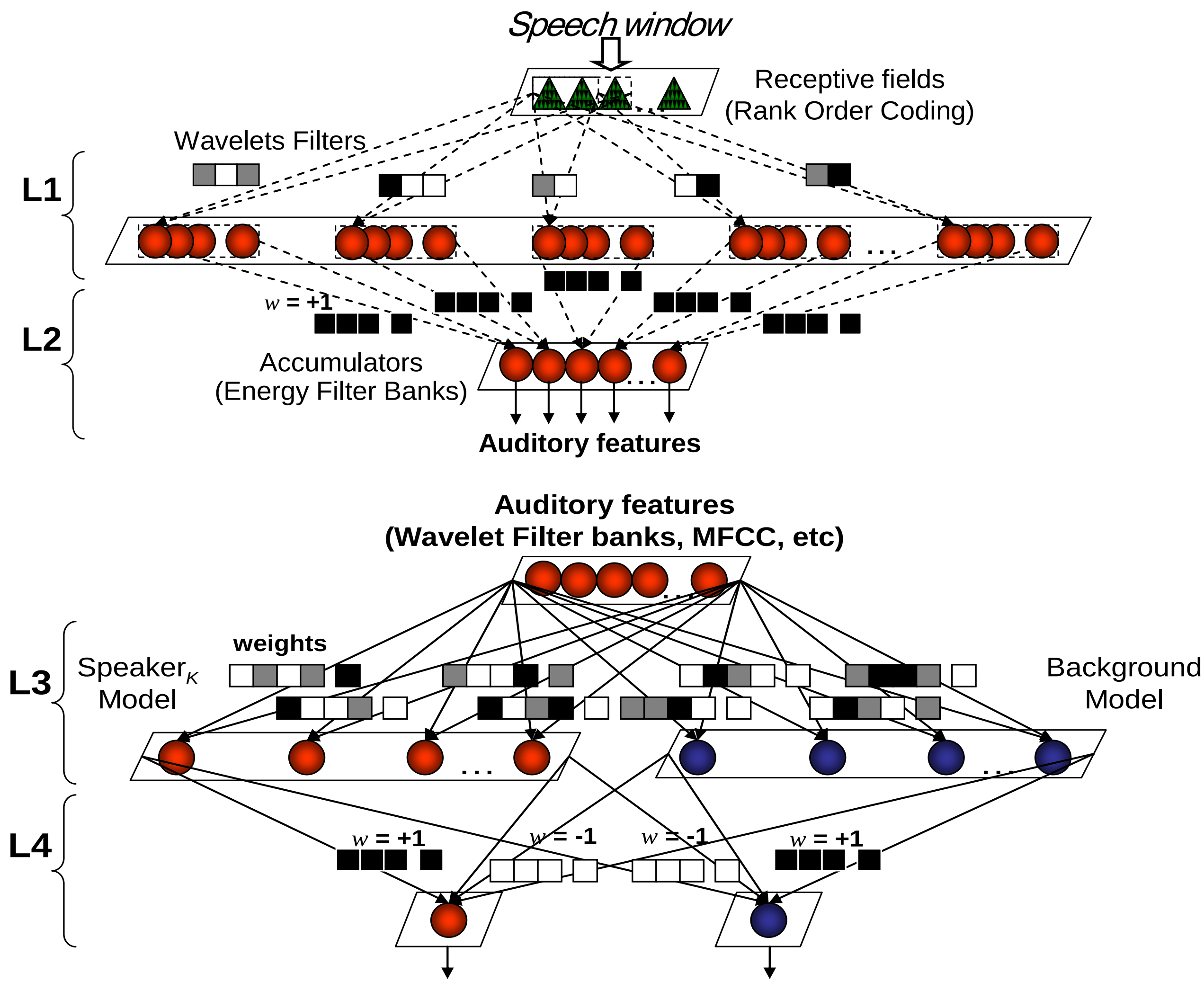
seSNN for person authentification based on face image data

(Wysoski, Benuskova, Kasabov, Proc. ICANN 2006, Springer LNCS, 2006)



seSNN for speaker authentification

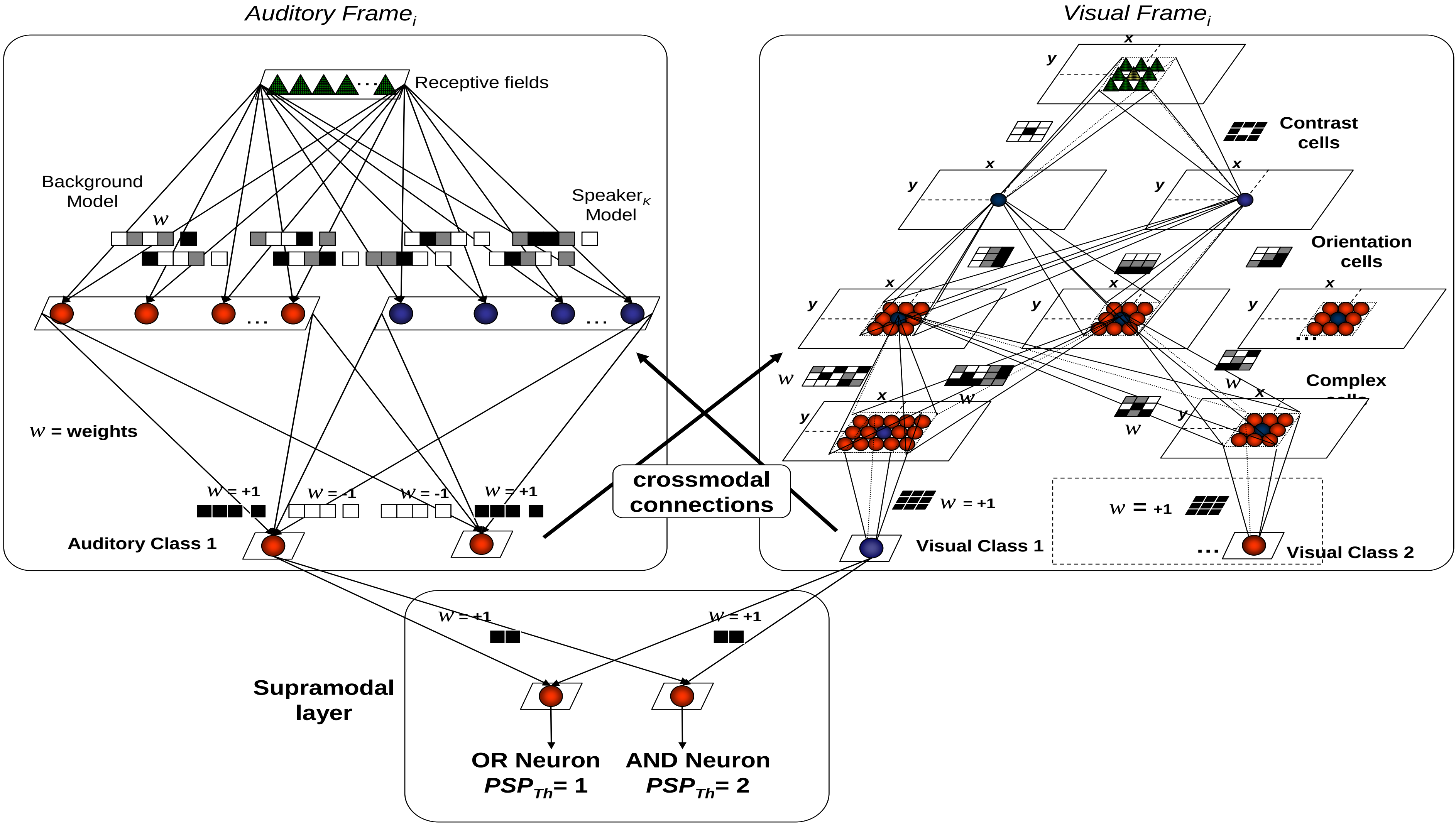
(Wysoski, Benuskova, Kasabov, Proc. ICANN 2007, Springer, LNCS, 2006)



seSNN for integrated audio-visual information processing

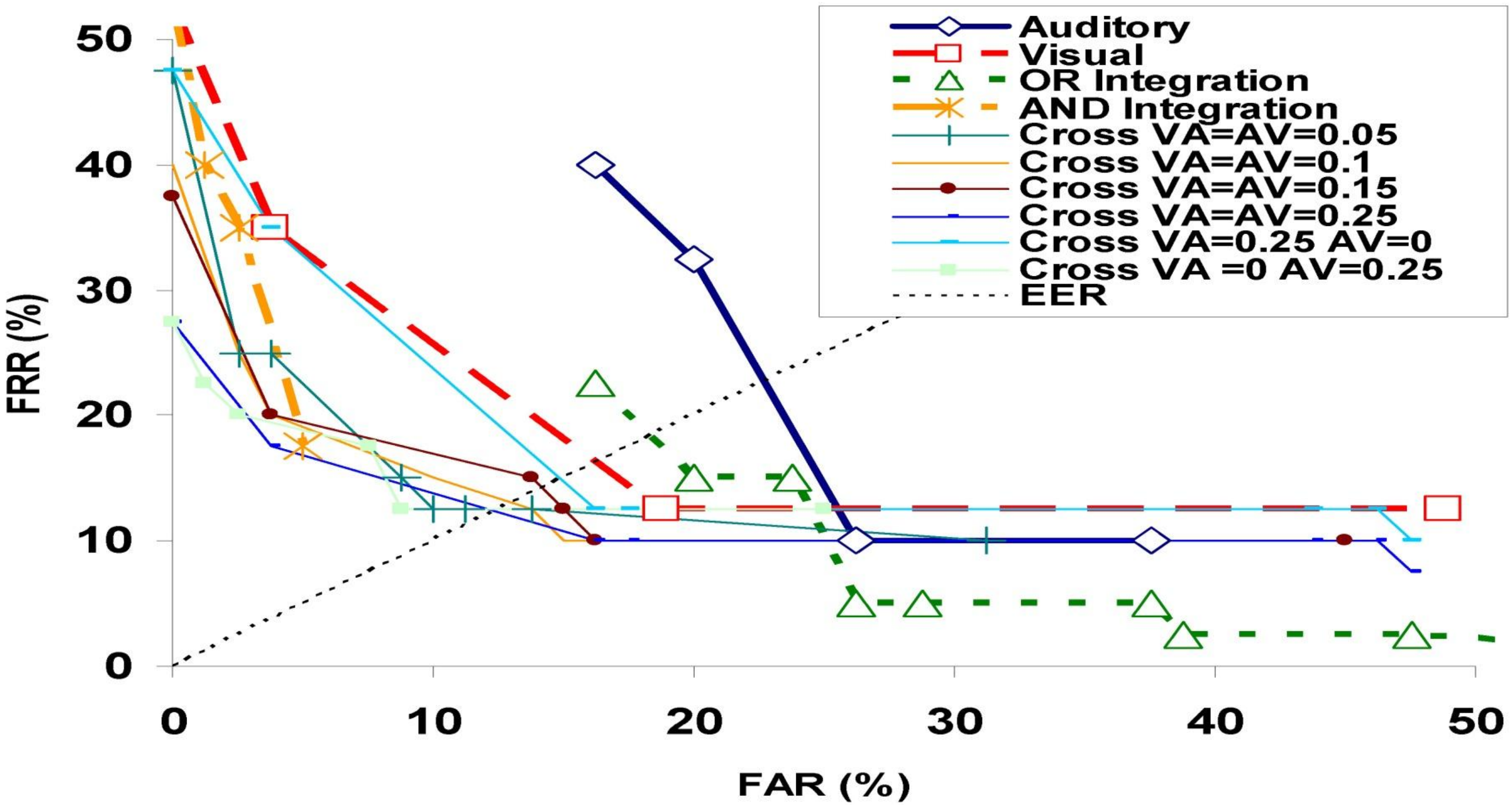
Person authentication based on auditory and visual information

(Wysoski, Benuskova and Kasabov, Proc. ICONIP, 2007, LNCS, and *Neural Networks*, 2010)



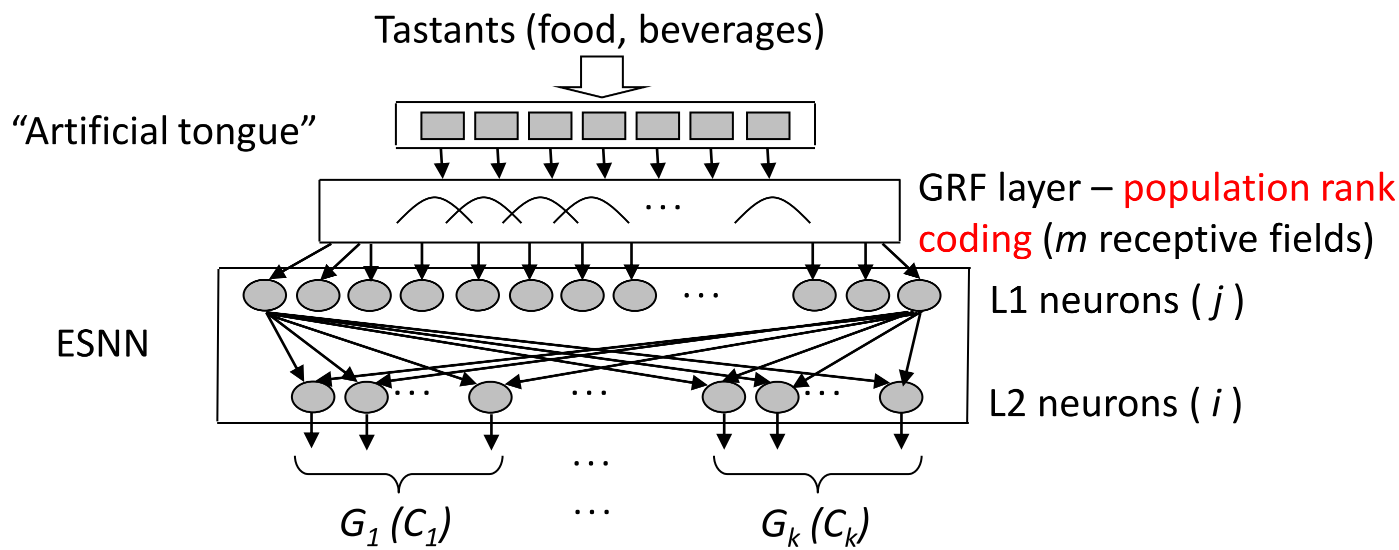
Using muti-modal audio-visual information reduces the error rate

VidTimit data base; (10 persons +2 imposters) x 4 attempts each.



seSNN for taste recognition

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

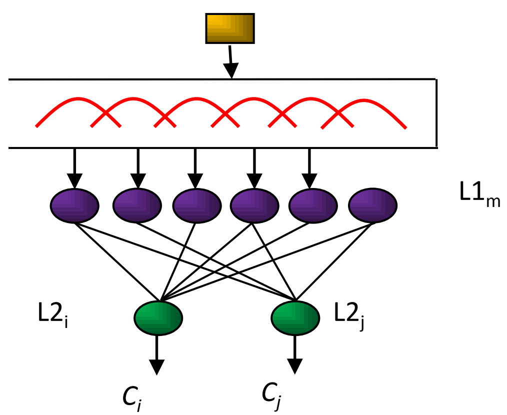


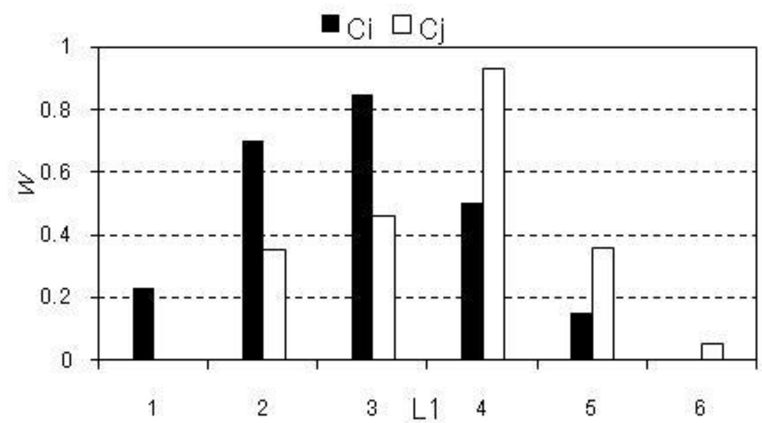
- The L2 layer evolves during the learning stage (S_{Θ}).
- Each class C_i is represented with an ensemble of L2 neurons
- Each ensemble (G_i) is trained to represent one class.
- The latency of L2 neurons' firing is decided by the order of incoming spikes.

Knowledge discovery through seSNN

(S.Soltic and N.Kasabov, *Int.J.Neural Systems*, 2010)

The eSNN architecture can be analysed for new information discovery at several levels:
- Feature subset selection (important variables are discovered for the problem in hand);
- The (optimised) parameters can be interpreted in the context of the problem;
- Association rules can be extracted from the trained eSNN structure (the eSNN learn through clustering), e.g.:





$$IF \quad v \text{ is } SMALL \quad THEN\ C_i$$

$$IF \quad v \text{ is } LARGE \quad THEN\ C_j$$

seSNN – advantages and problems

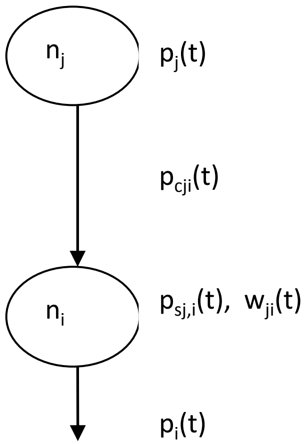
Advantages:

- Fast on-line learning;
- Simple neuronal model;
- Simple structure – only 3 parameters;
- Accumulation of information over time from incoming frames;
- Good synchronisation between modules;
- Both feature extraction and learning is realised in a uniform structure.

Problems:

• Too simple IF model of a neuron;
• Too simple SNN structure (no recurrent connections; no complex evolvability);
• No optimisation of the neuronal parameters;
• No feature selection;
• Too rough feature extraction scheme using digital spiking neurons to implement analogue filters;
• Deterministic structure of the seSNN;
• Limited spatio-temporal pattern recognition (STPR) abilities.

3. Probabilistic evolving SNN (peSNN)



Probabilistic spiking neuron model, pSNM (*Kasabov, Neural Netw., 2010).*

The information in pSNM is represented as both connection weights and probabilistic parameters for spikes to occur and propagate. The neuron (n_i) receives input spikes from pre-synaptic neuron n_j ($j=1,2,\dots,m$). The state of neuron n_i is described by the sum of the inputs received from all *m* synapses – the postsynaptic potential, PSPi(t). When PSPi(t) reaches a firing threshold $\vartheta i(t)$, neuron ni fires, i.e. emits a spike.

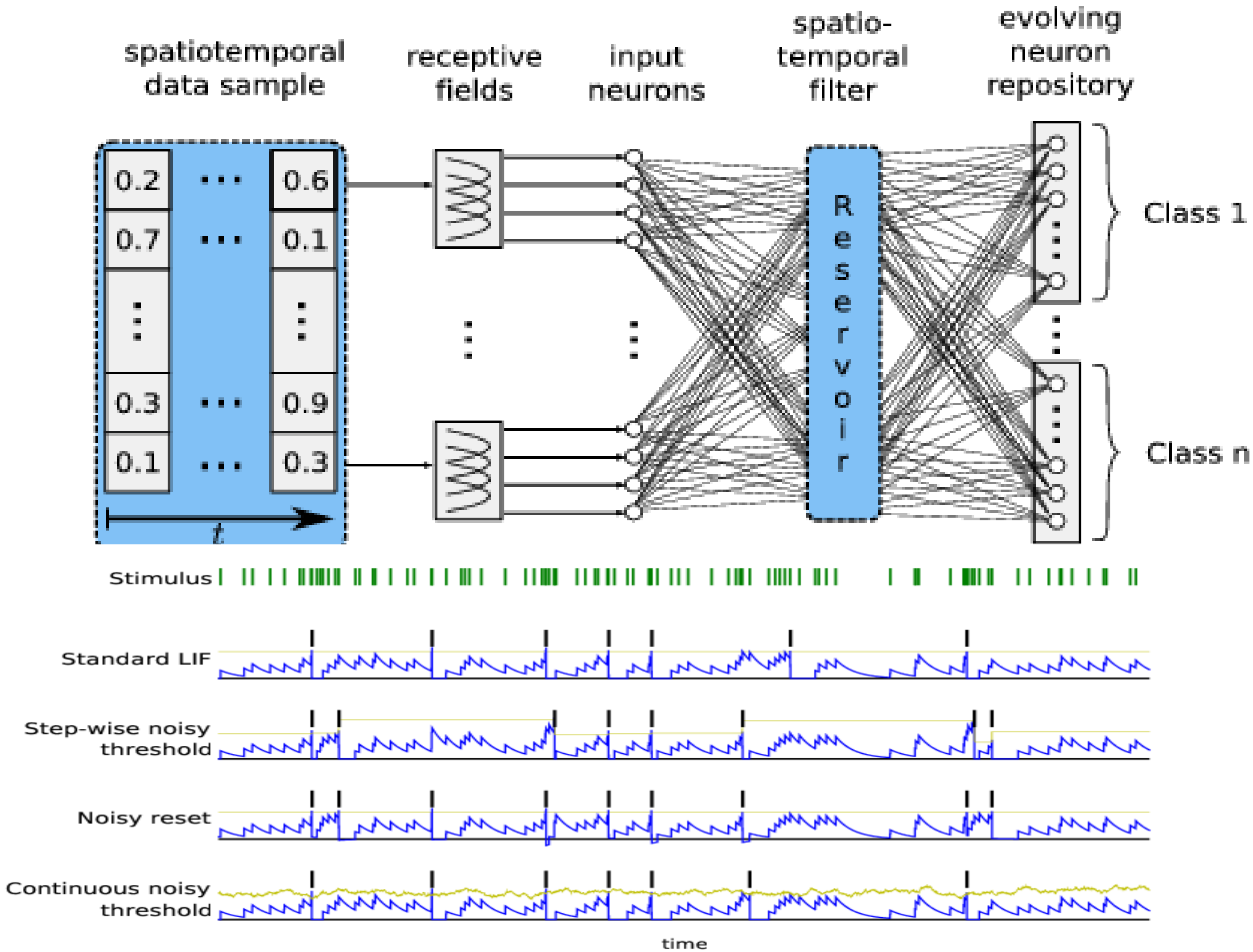
The PSPi(t) is now calculated using a new formula:

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

where: e_j is 1, if a spike has been emitted from neuron n_j, and 0 otherwise; $g(p_{cj,i}(t))$ is 1 with a probability $p_{cji}(t)$, and 0 otherwise; $f(p_{sj,i}(t))$ is 1 with a probability $p_{sj,i}(t)$, and 0 otherwise; t_0 is the time of the last spike emitted by n_i; $\eta(t-t_0)$ is an additional term representing decay in the PSP. As a special case, when all or some of the probability parameters are fixed to "1", the ipSNM will be simplified and will resemble some already known spiking neuron models, such as SRM.

peSNN for STP recognition

S. Schliebs, N. Nuntalid, and N. Kasabov,Towards spatio-temporal pattern recognition using evolving spiking neural networks, Proc. ICONIP 2010, Springer LNCS, 2010

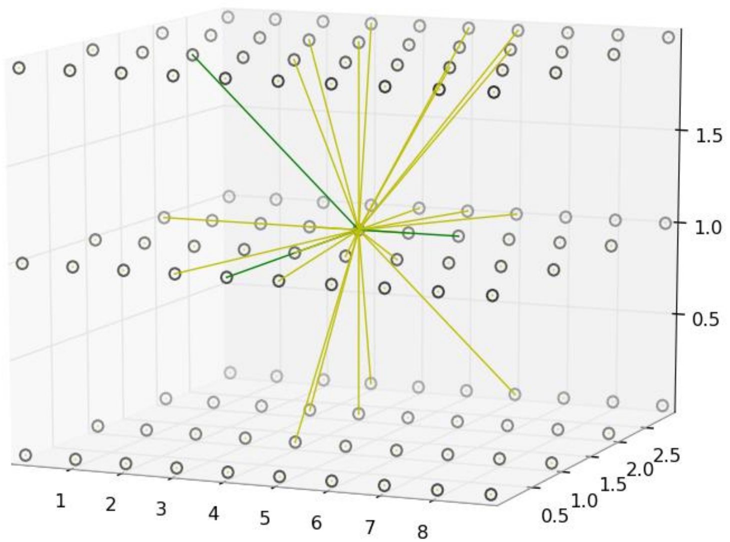


Connectivity in the Reservoir of the epSNN

- 1000 neurons connected in a 3D grid as 10x10x10
- Excitatory 80%, Inhibitory 20%; Small world connections:

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

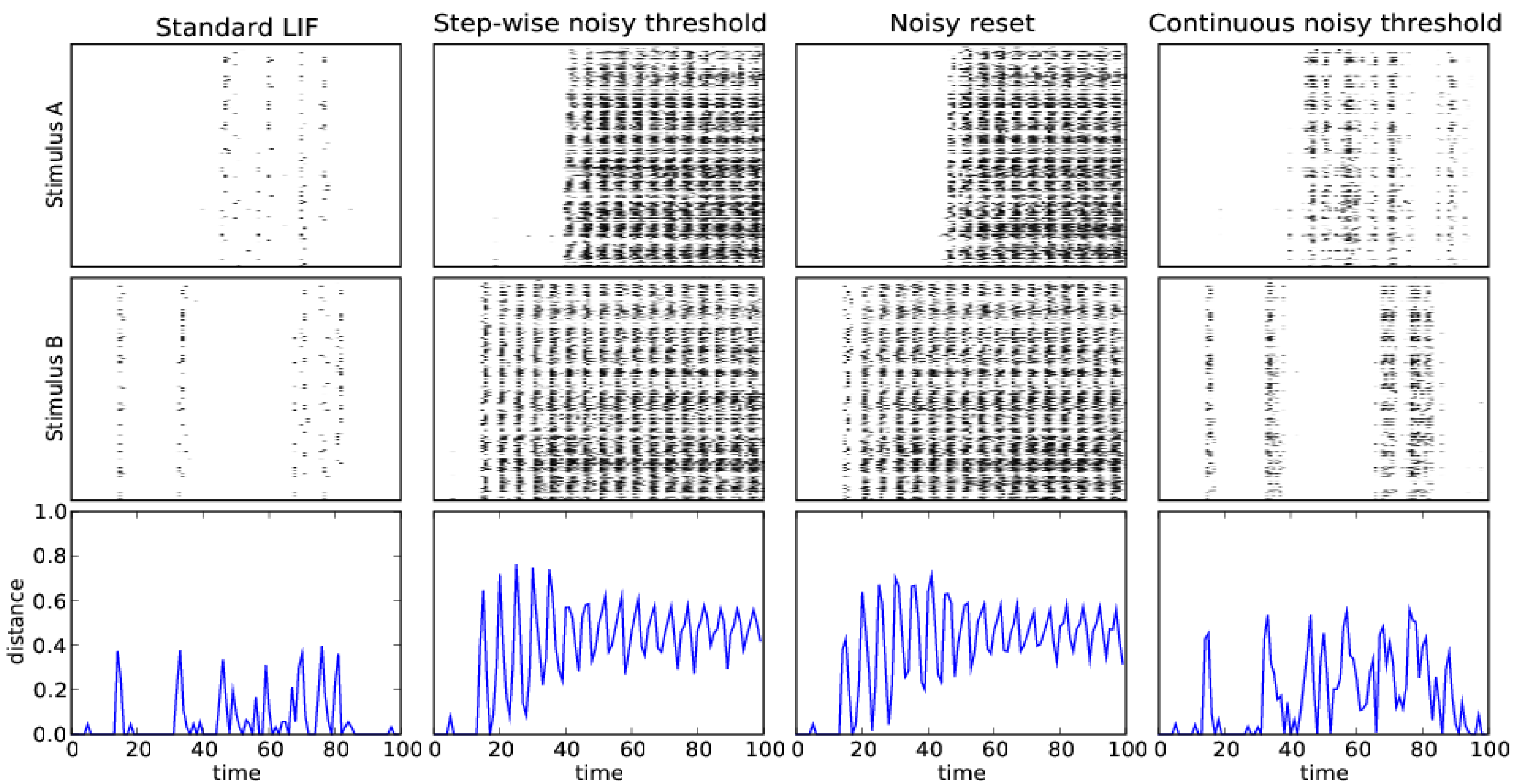
- *Maass, W., Natschl¨ager, T., Markram, H.: Real-time computing without stable states: A new framework for neural computation based on perturbations. Neur. Comp. 14(11),2531–60, 2002; and*
- *Wojcik and et al,2009, Which Model to use for the LSM?*



peSNN for STP recognition on a bench mark data

Experimental settings:

- Two spiking sequences A and B are independently generated 25 times by a Poisson process with 200Hz mean rate (*Grzyb, B.J., Chinellato, E., Wojcik, G.M., Kaminski, W.A.: Which model to use for the liquid state machine? In: Proc. IJCNN'09, pp. 1692–1698. IEEE Press, 2009).*

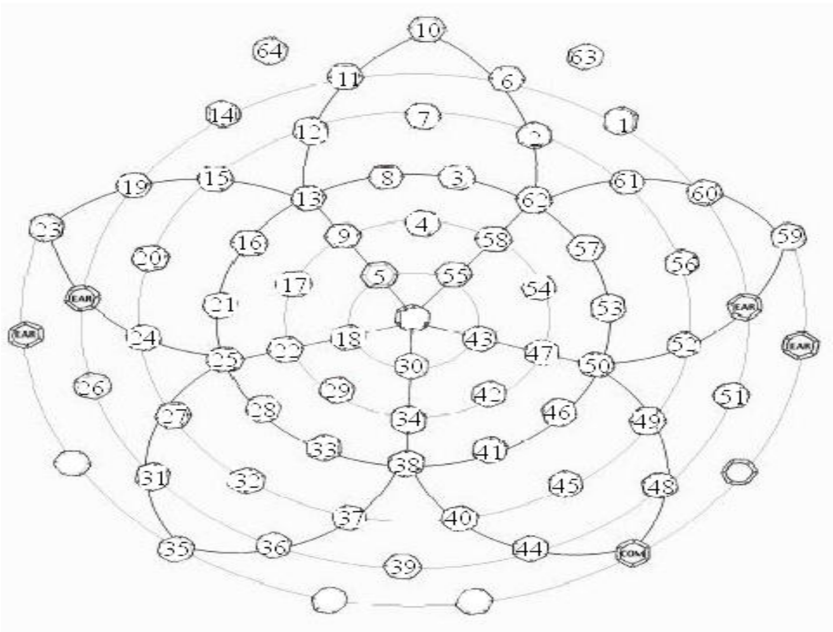


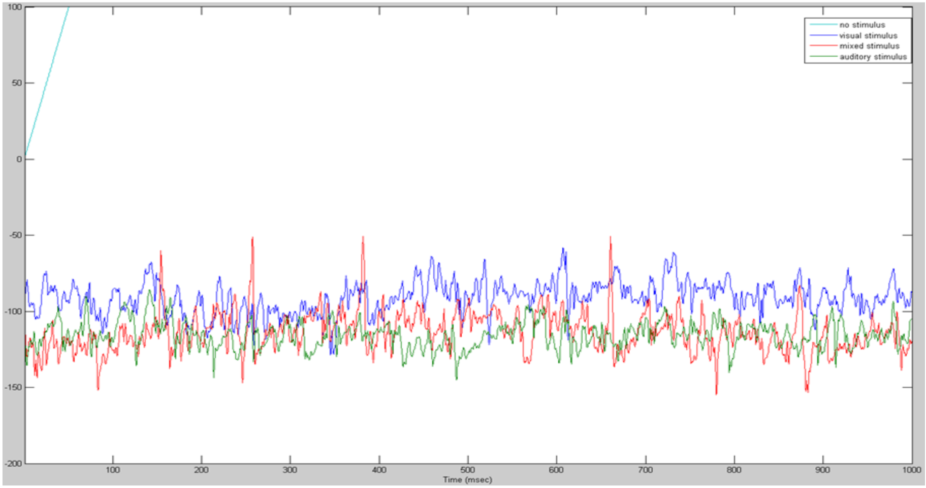
Work in progress: peSNN for complex EEG STP recognition

Case study 1: Four classes of brain perception states are used with 37 single trials each of them including the following stimuli (With van Leuwen, Cihotcky, et al, RIKEN, BSI, Tokyo)

- Class1 - Auditory Stimulus;
- Class2 - Visual Stimulus;
- Class3 - Mixed Auditory and visual stimuli;
- Class 4 - No stimulus.

Case study 2: Person identification based on EEG data.





Work in progress: peSNN for state-dependent computations (FA)

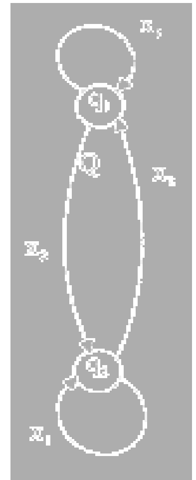
f_1

X(t)	Q(t)	Q(t+1)
x_1	q_1	q_1
x_1	q_2	q_2
x_2	q_1	q_2
x_2	q_2	q_1

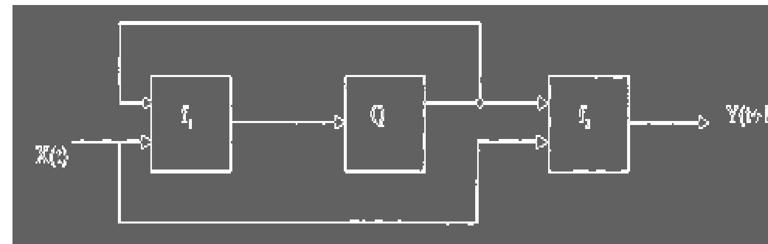
f_2

X(t)	Q(t)	Y(t+1)
x_1	q_1	y_2
x_1	q_2	y_1
x_2	q_1	y_1
x_2	q_2	y_1

(a)

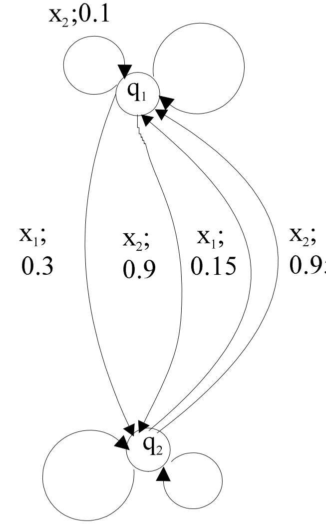


(b)

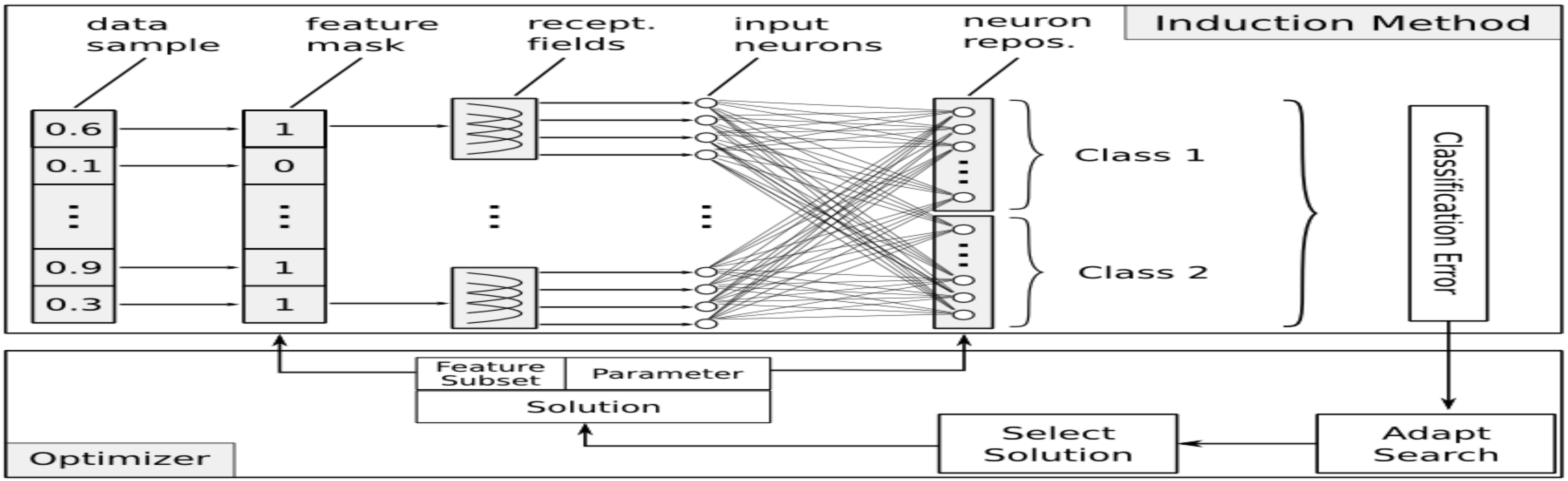


(c)

Challenges:
- How to represent stable states and state transitions?
- How to achieve a larger number of states?
- Can we utilize polychronization states?
- FA synthesis as a SNN;
- Learning FA from data and extracting it from the SNN.
- How to apply the rich theory of FA developed so far?
- Deterministic vs probabilistic FA;
- Pilot applications.



4. Probabilistic quantum inspired eSNN (pqeSNN)



1) The principle of quantum probability feature representation:
At any time a feature is both present and not present in a computational model, which is defined by the probability density amplitudes. When the model computes, the feature state is 'collapsed' in either 0 (not used) or 1 (used).

2) Quantum probability representation of the connections per the peSNN.

3) Quantum probability representation of the eSNN parameters.

N.Kasabov, Integrative connectionist learning systems inspired by Nature: Current models, future trends and challenges, Natural Computation, Springer, 2009, 8:199-218.

*qi E*volutionary Algorithms compute probability functions rather than single vectors (points in the problem space)

- QiEA use a q-bit representation of a chromosome of n "genes" at a time t:

$$Q(t) = \{q_1^t, q_2^t, \ldots, q_n^t\}$$

- Each q-bit is defined as a pair of numbers (*α, β*) – probability density amplitudes.

$$|\alpha_i|^2 + |\beta_i|^2 = 1$$

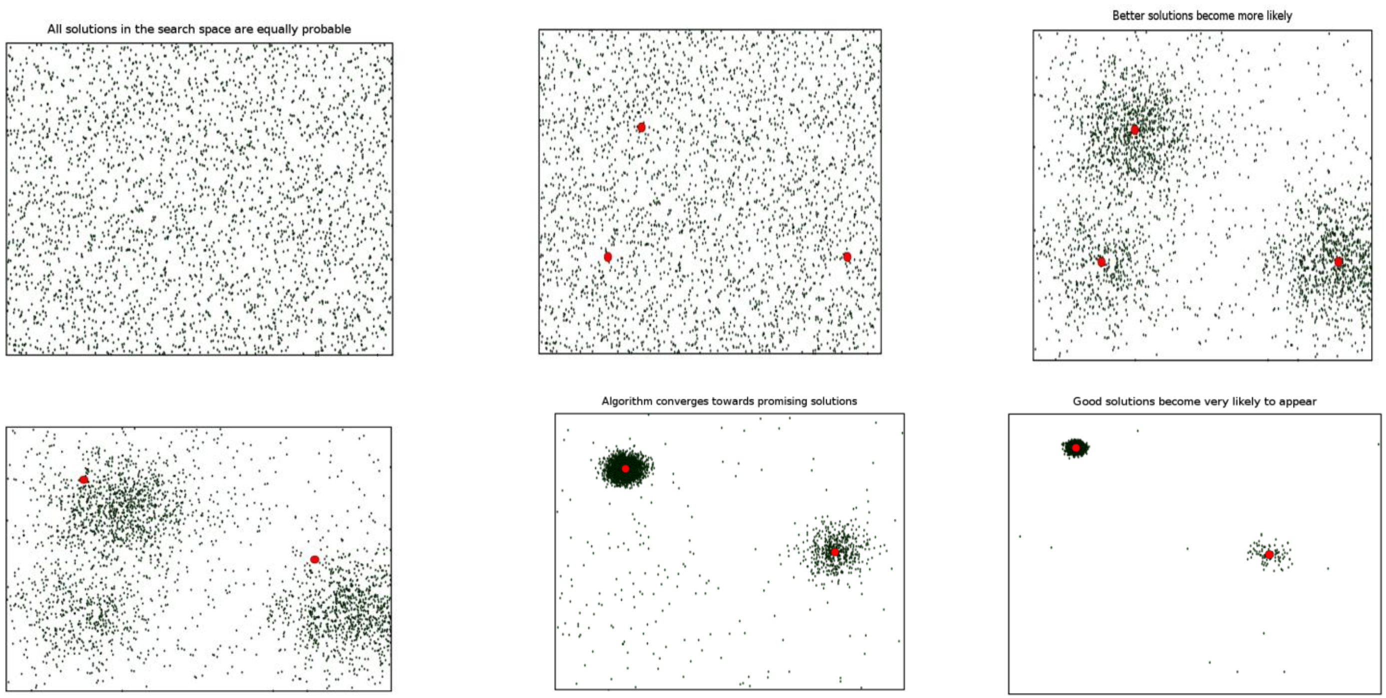
- A *n* element q-bit vector can represent probabilistically 2^n states at any time
- The output is obtained after the q-bit vector is collapsed into a single state
- Changing probability density with quantum gates, e.g. rotation gate:

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_{t-1} \\ \beta_{t-1} \end{bmatrix}$$

- Evolutionary computing with q-bit representation has a better characteristic of population diversity than other representations, since it can represent linear superposition of states probabilistically .

Versatile QiEA (vQiEA) compute multiple probability functions (Multimodel EDA)

M. Defoin-Platel, S.Schliebs, N.Kasabov, Quantum-inspired Evolutionary Algorithm: A multi-model EDA, IEEE Trans. Evolutionary Computation, Dec., 2009



The (v)QEA consists of three different interacting levels: the quantum individual, -group and -population levels. The group level corresponds to attractors.

A hypothetical example of state convergence to local minima for a system described by a qbit register (chromosome) over 5 applications of a rotation quantum gate operator. The darker points represent system states described by the qubit vector that have a higher probability of occurrence.

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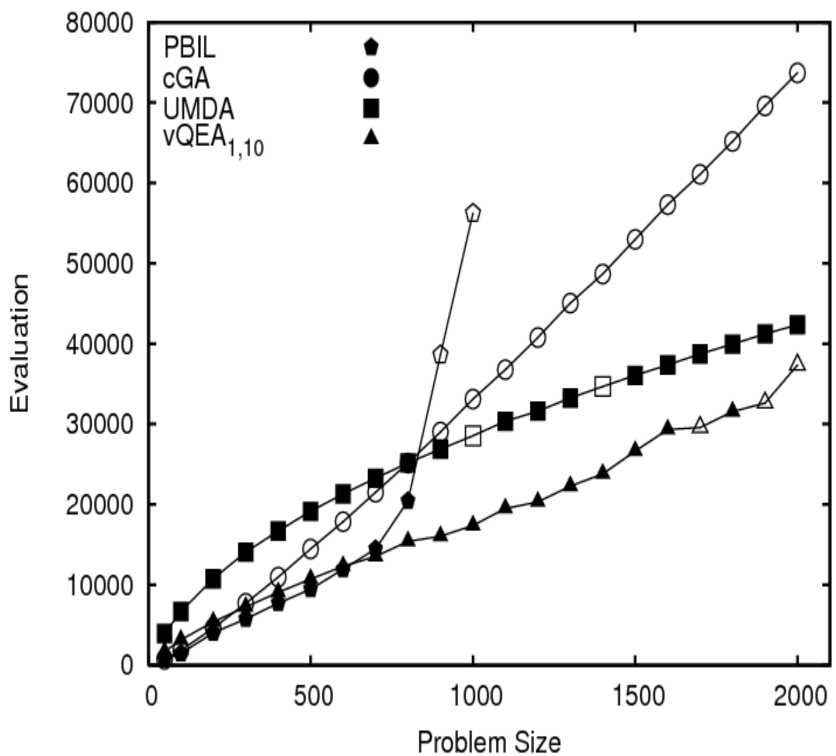
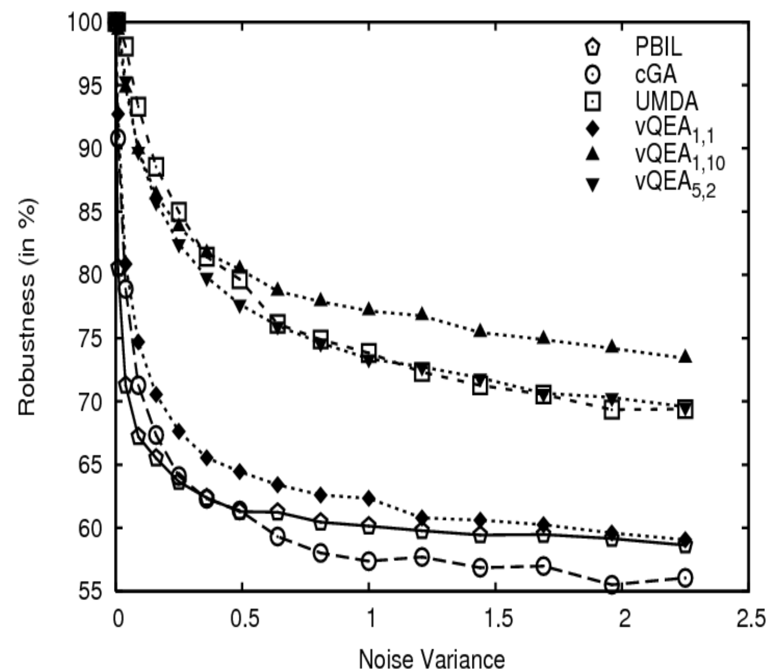
...vQiEA

Time complexity and scalability



Computability in the presence of noise

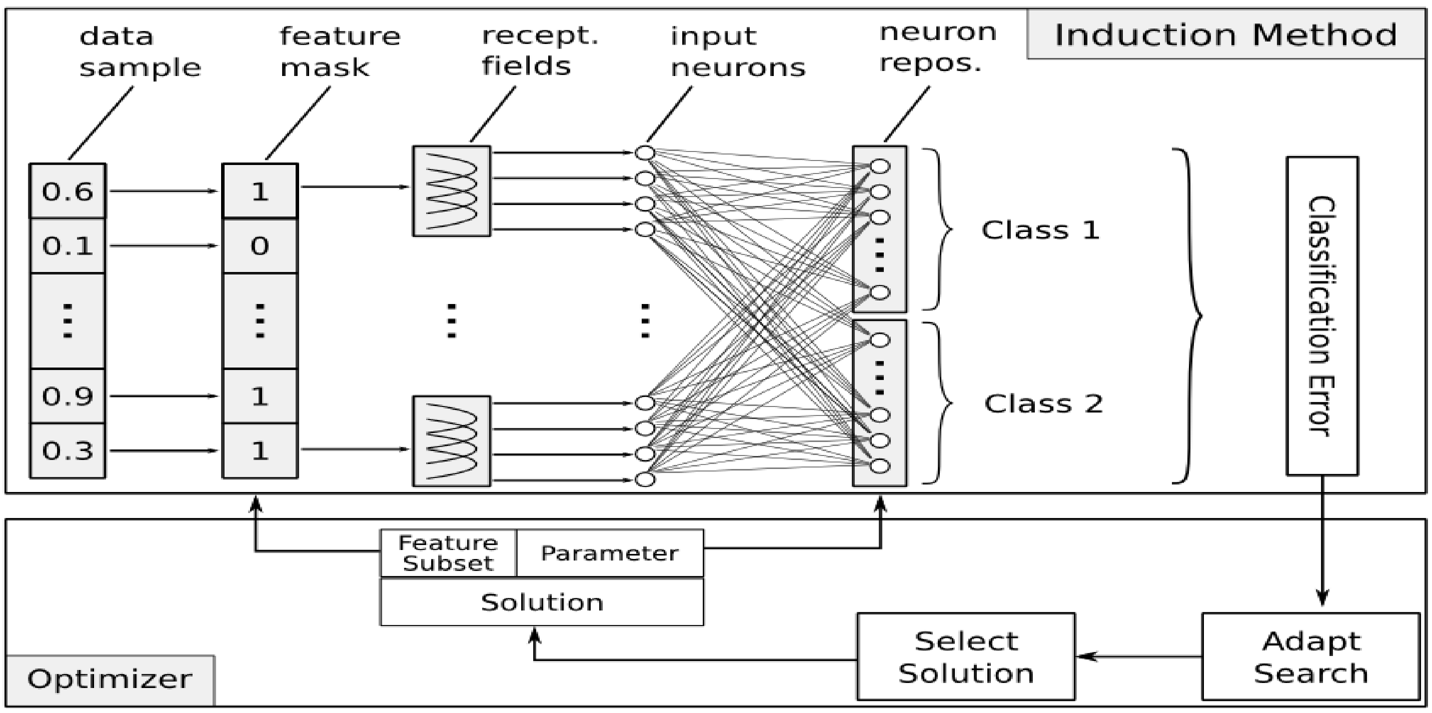


Integrated feature selection and parameter optimisation of pqeSNN for classification

S.Schliebs, M.Defoin-Platel and N.Kasabov, ICONIP'2008 and Neural Networks, 2010

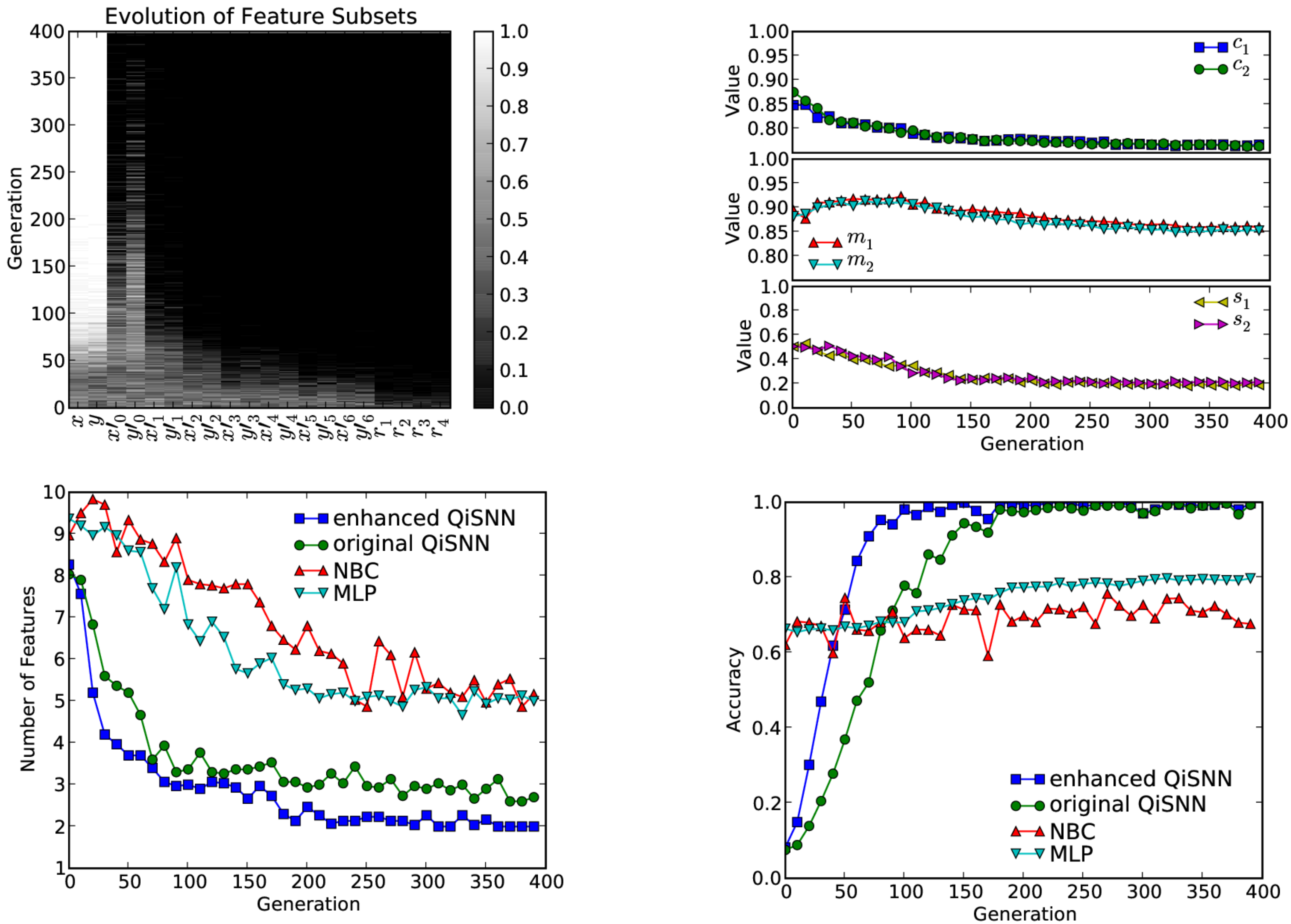
Results:

- Minimised structural complexity (features and connections);
- Maximised accuracy and speed ;
- Optimised SNN architecture;
- Knowledge discovery (important features).

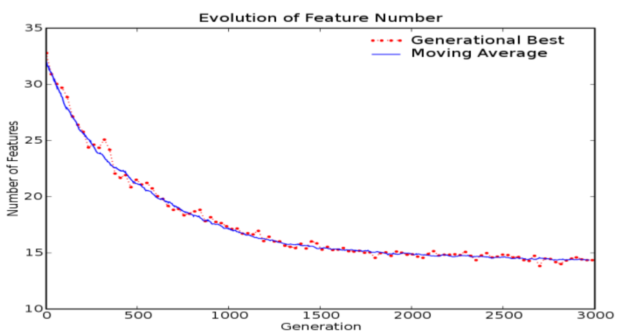
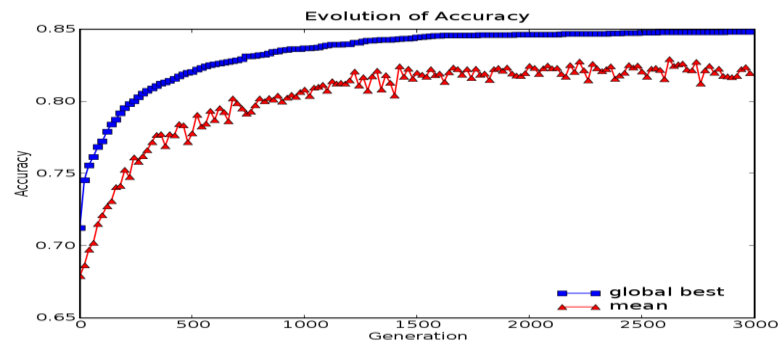


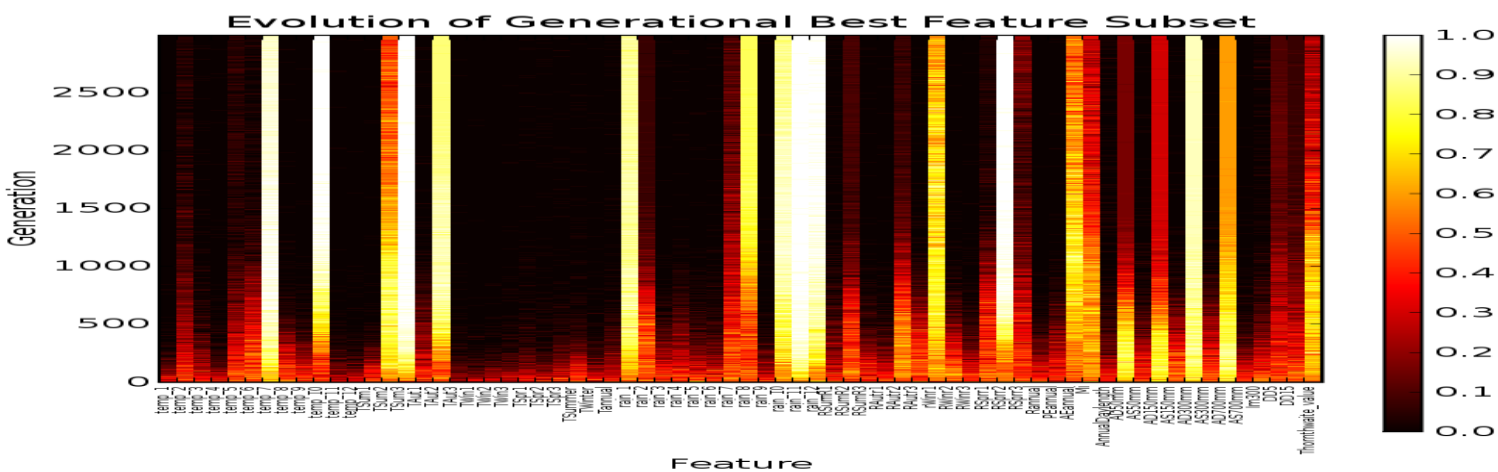
Benchmark classification problem (spiral data)

(Schliebs, Kasabov, Proc. IJCNN 2009 and Neural Networks, 2009)



Feature selection in ecological modelling (insect establishment prediction)

	
Evolution of classification accuracy on the climate data set after 3,000 generations.	Evolution of the features on the climate data set. The best accuracy model is obtained for 15 features .



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Quantum Inspired PSO (QiPSO)

- Quantum inspired Particle Swarm Optimization (QiPSO) proposed by Han and Kim (2002)
- The main idea of QiPSO is to use a standard PSO function to update quantum angle θ
- The velocity update formula in standard PSO is modified to get a new quantum angle which is translated to the new probability of the qubit as follows:

$$\Delta\theta_n = w * \Delta\theta_{n_{t-1}} + c_1 * rand() * (\theta_{gbest_n} - \theta_n) + c_2 * rand() * (\theta_{pbest_n} - \theta_n)$$

- Then, based on the new θ, new probabilities α and β are calculated using a rotation gate as follows:

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta) & -\sin(\Delta\theta) \\ \sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \begin{bmatrix} \alpha_{t-1} \\ \beta_{t-1} \end{bmatrix}$$

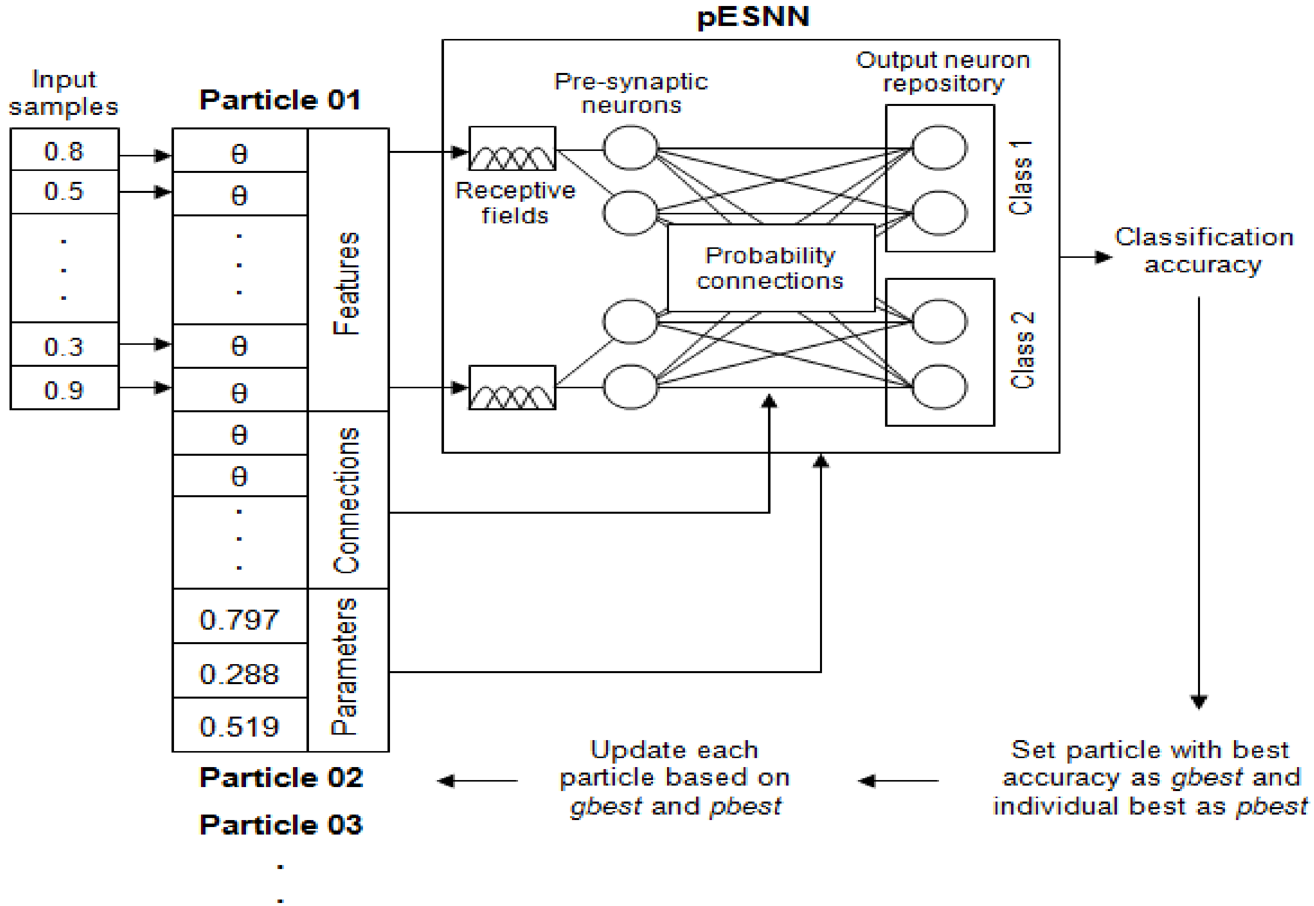
equivalently: $\theta = \theta_{t-1} + \Delta\theta$

where θ is the new quantum angle of the quantum particle position.

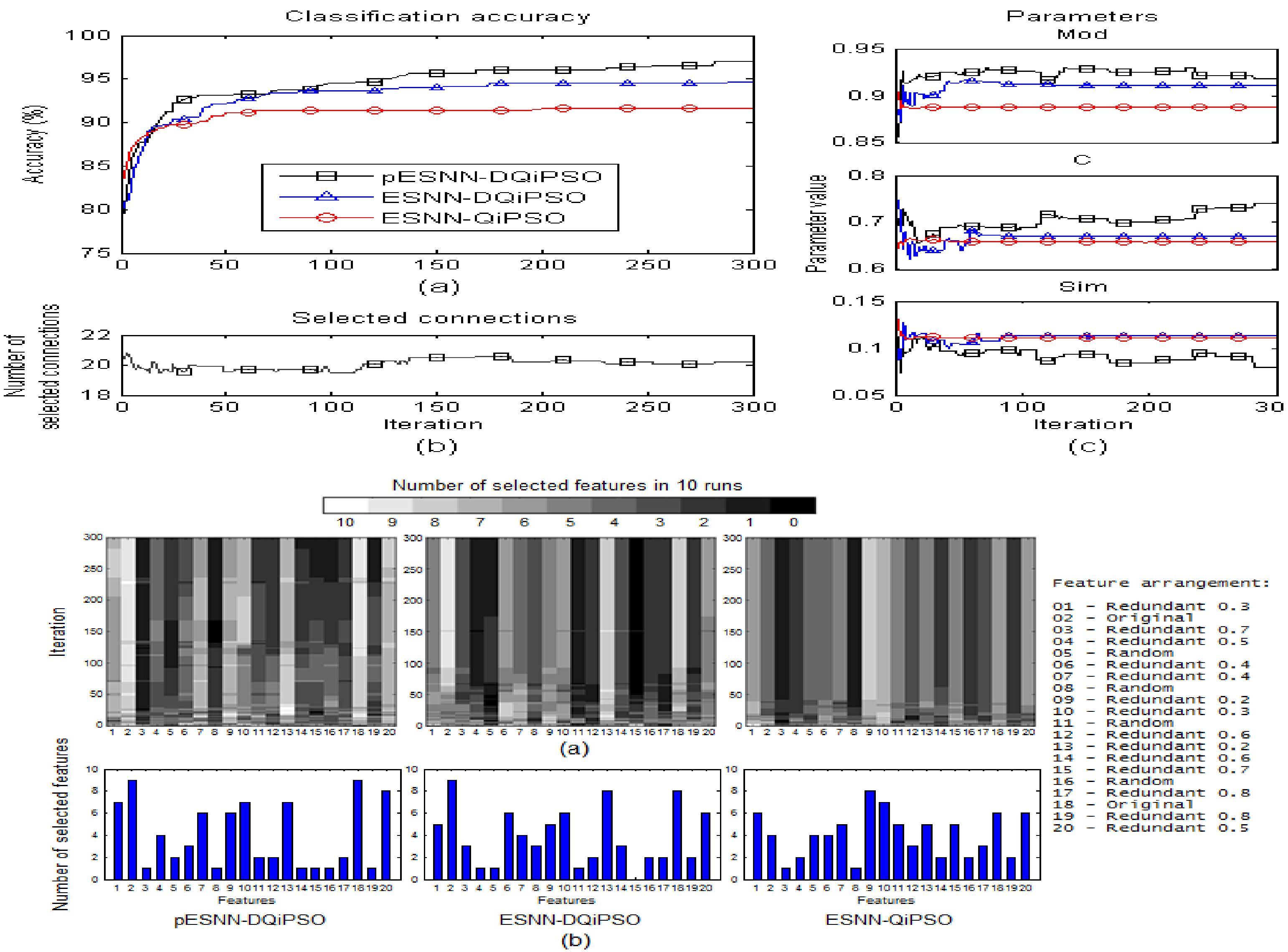
- QiPSO computes multiple probability functions

Feature, parameter and *connectivity* !!! optimisation of a pqeSNN

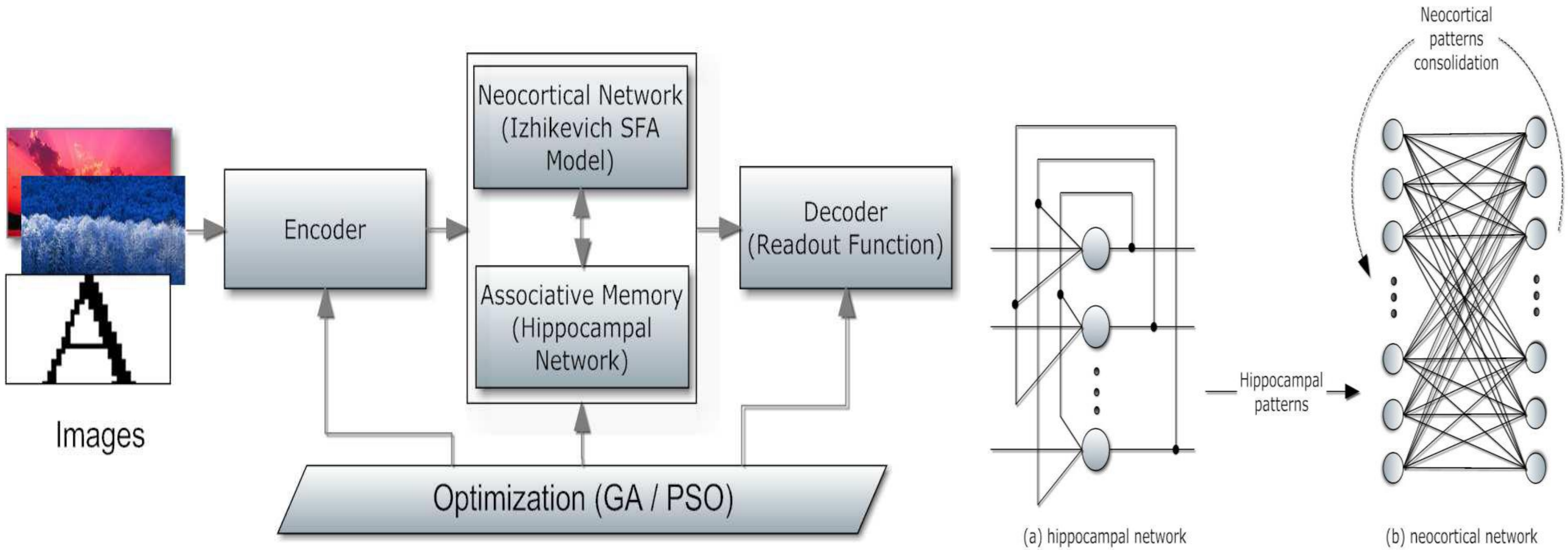
H. Nuzly, N. Kasabov, S. Shamsuddin, Probabilistic Evolving Spiking Neural Network Optimization Using Dynamic Quantum Inspired Particle Swarm Optimization, Proc. ICONIP 2010, LNCS, 2010



Again, the 2-spiral classification benchmark problem, but this time optimising the *probabilistic connections* as well.



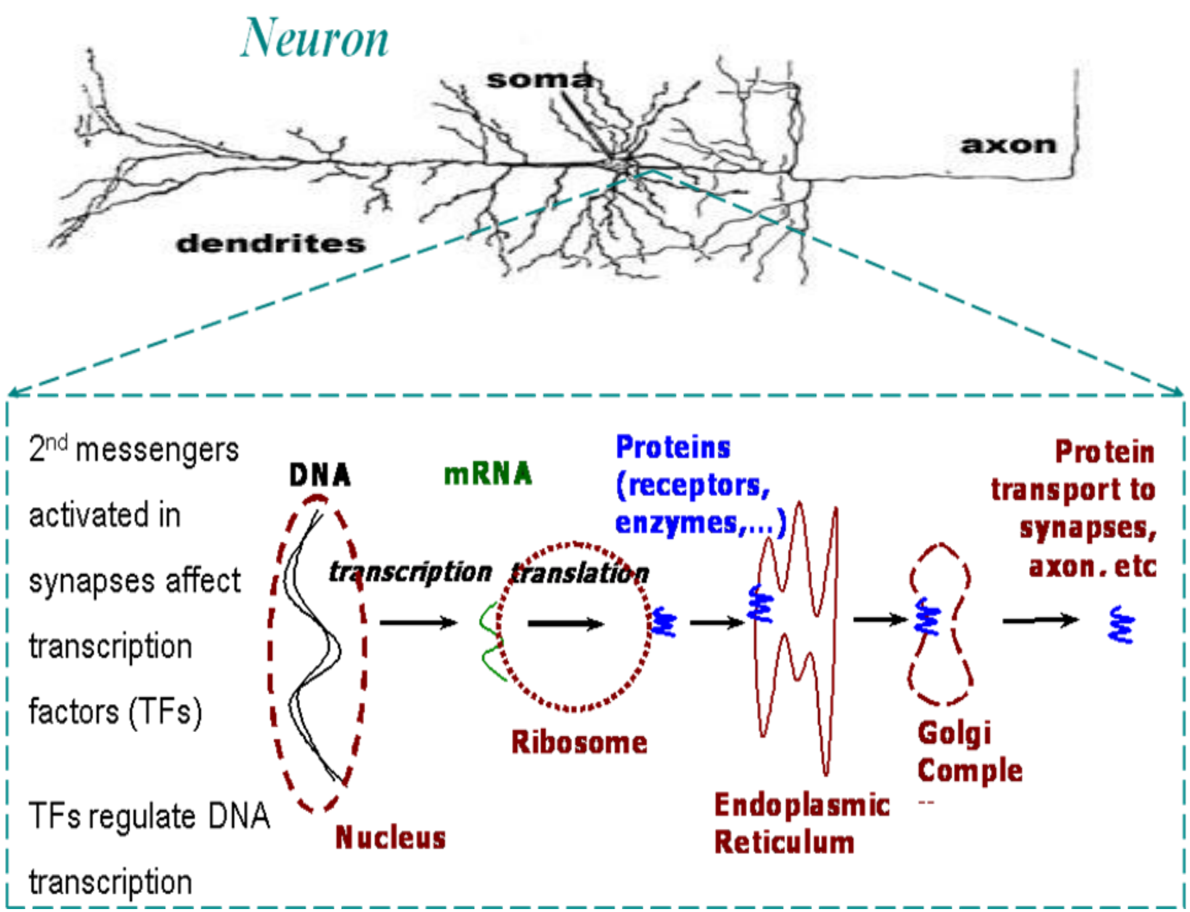
Work in progress: peSNN for Associative Memories



Challenges:

- How to achieve much larger capacity when compared to Hopfield networks?
- Can we utilize the large number of polychronization states?
- STP storage and retrieval (rather than single vectors)?

5. Neurogenetic evolving SNN (ngeSNN)



Gene information processing principles:

- Nature via Nurture
- Complex interactions between thousands of genes (appr. 6000 expressed in the brain) and proteins (more than 100,000)
- Different time-scales
- Stochastic processes

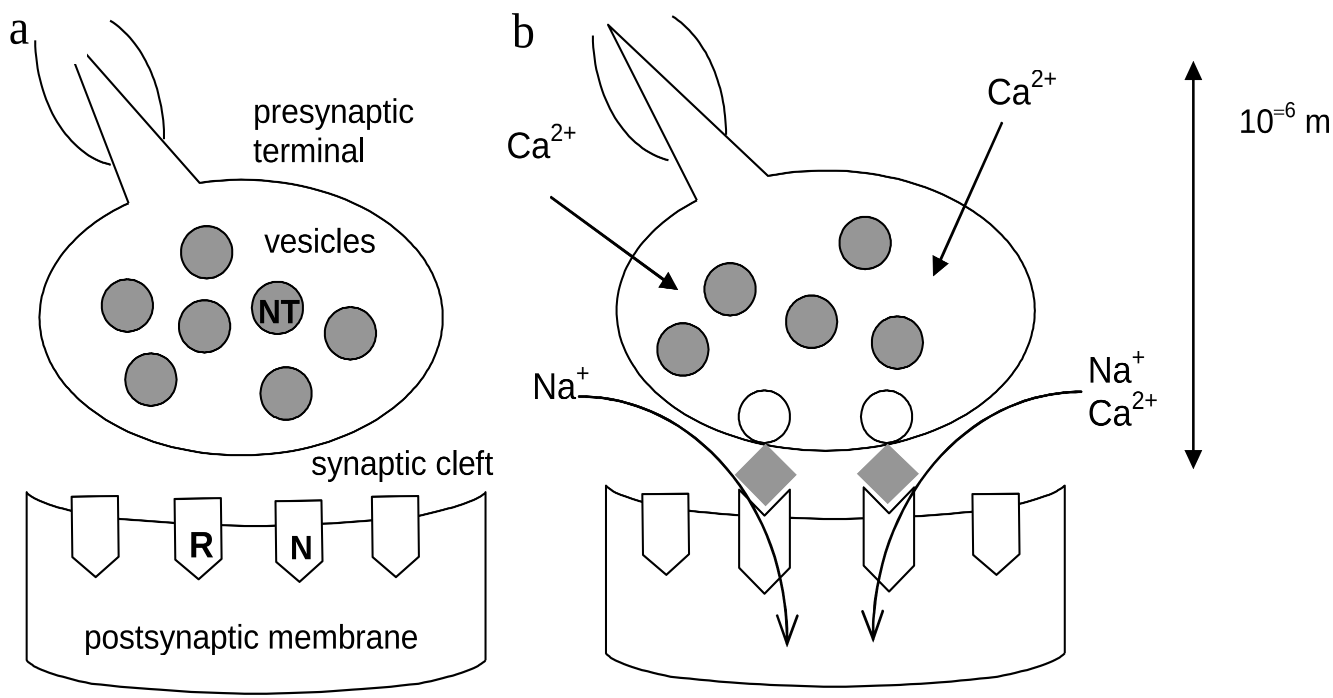
Offer the potential for:

- Integrating molecular and neuronal information processing (possibly with particle level as well)

The challenge:

How do we integrate molecular and spiking neuronal processes in a SNN?

Molecular (protein) level of spiking activities



Scheme of synaptic transmission:

a) A synapse is ready to transmit a signal.

b) Transmission of electric signal in a chemical synapse upon arrival of action potential into the terminal.

Abbreviation: NT = neurotransmitter, R = AMPA-receptor-gated ion channel for sodium, N = NMDA-receptor-gated ion channel for sodium and calcium.

Gene/Protein Regulatory Networks (GRN) relate to spiking activities

Functions of neurons and neural networks are influenced by internal networks of connected and interacting genes – i.e. gene regulatory networks.

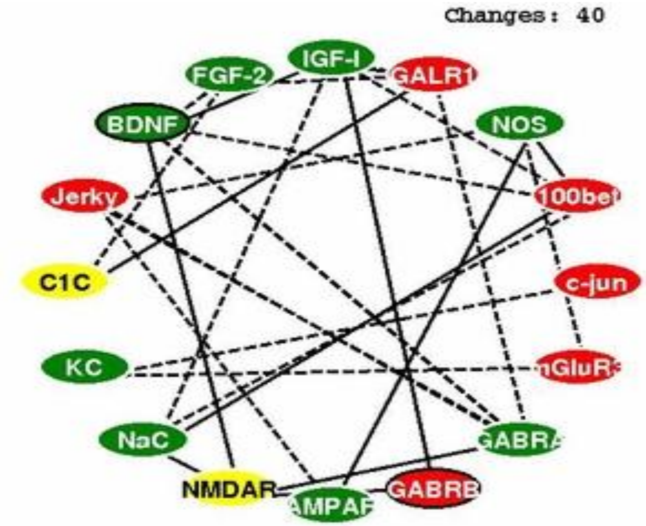


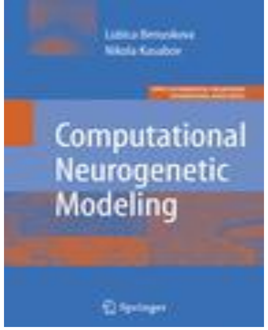
Table. Neuronal Parameters and Related Proteins

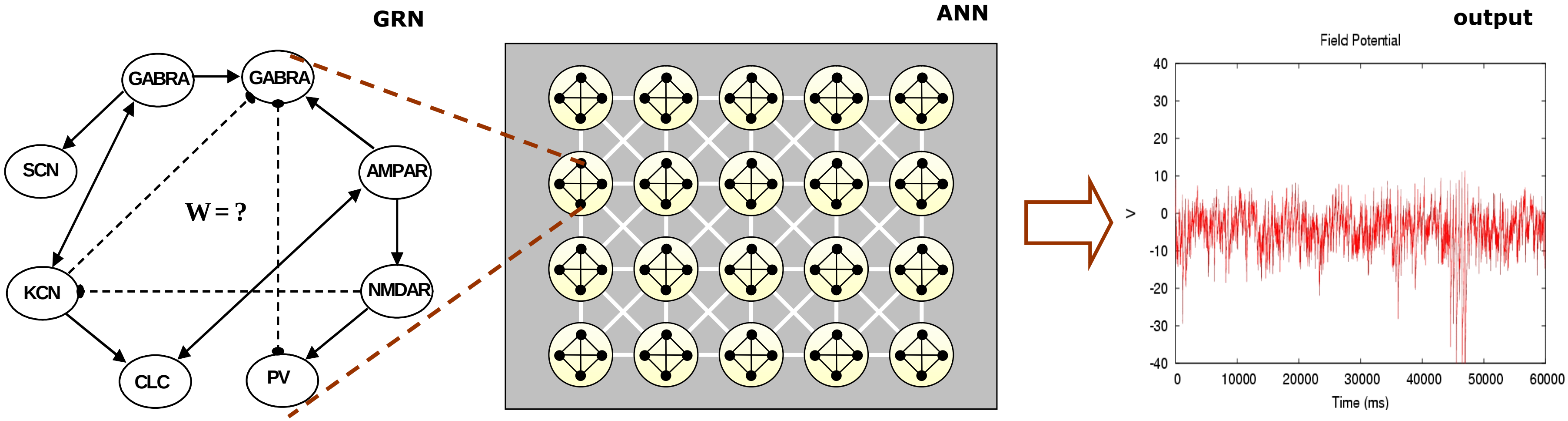
Neuronal parameter Amplitude and time constants of	Protein
Fast excitation PSP	AMPAR
Slow excitation PSP	NMDAR
Fast inhibition PSP	GABRA
Slow inhibition PSP	GABRB
Firing threshold	SCN, KCN, CLC
Late excitatory PSP through GABRA	PV

The challenge is how to integrate a GRN model into SNN

Computational Neurogenetic Modelling:

A neuro-genetic spiking neuron model (**ngSNM**) integrates two levels of computability and complexity – spiking and genetic.

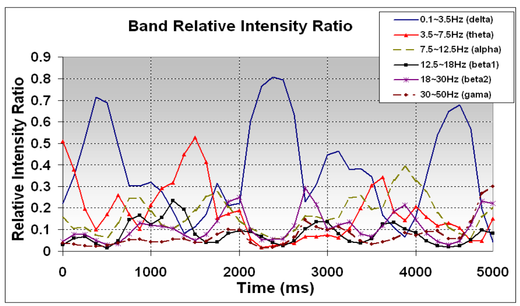




$$P_j(t) = P_j(0) g_j(t)$$

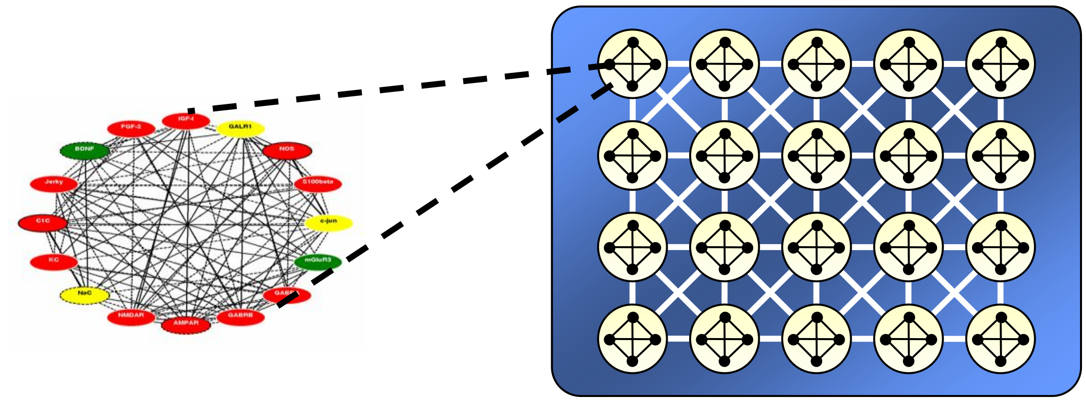
$$g_j(t+1) = \sigma\left(\sum_{k=1}^{n} w_{jk}(t) g_k(t)\right)$$

$$\varepsilon_{ij}^{type}(s) = A^{synapse}\left(\exp\left(-\frac{s}{\tau_{decay}^{type}}\right) - \exp\left(-\frac{s}{\tau_{rise}^{type}}\right)\right)$$



A ngeSNN is an eSNN that incorporates a gene regulatory network to capture the connection and interaction of several genes related to neuronal activities.

Work in progress: Integrative probabilistic ngeSNN



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

x1	x2	…	xn	q1	q2	..	qs	C11	C12	..	Cmm	P1	…	pm	g1	..	gk	L11	.. Lkk

Input features **eSNN p parameters** **eSNN connections** **Probability of neurons spiking** **Genes and their connections**

--- --

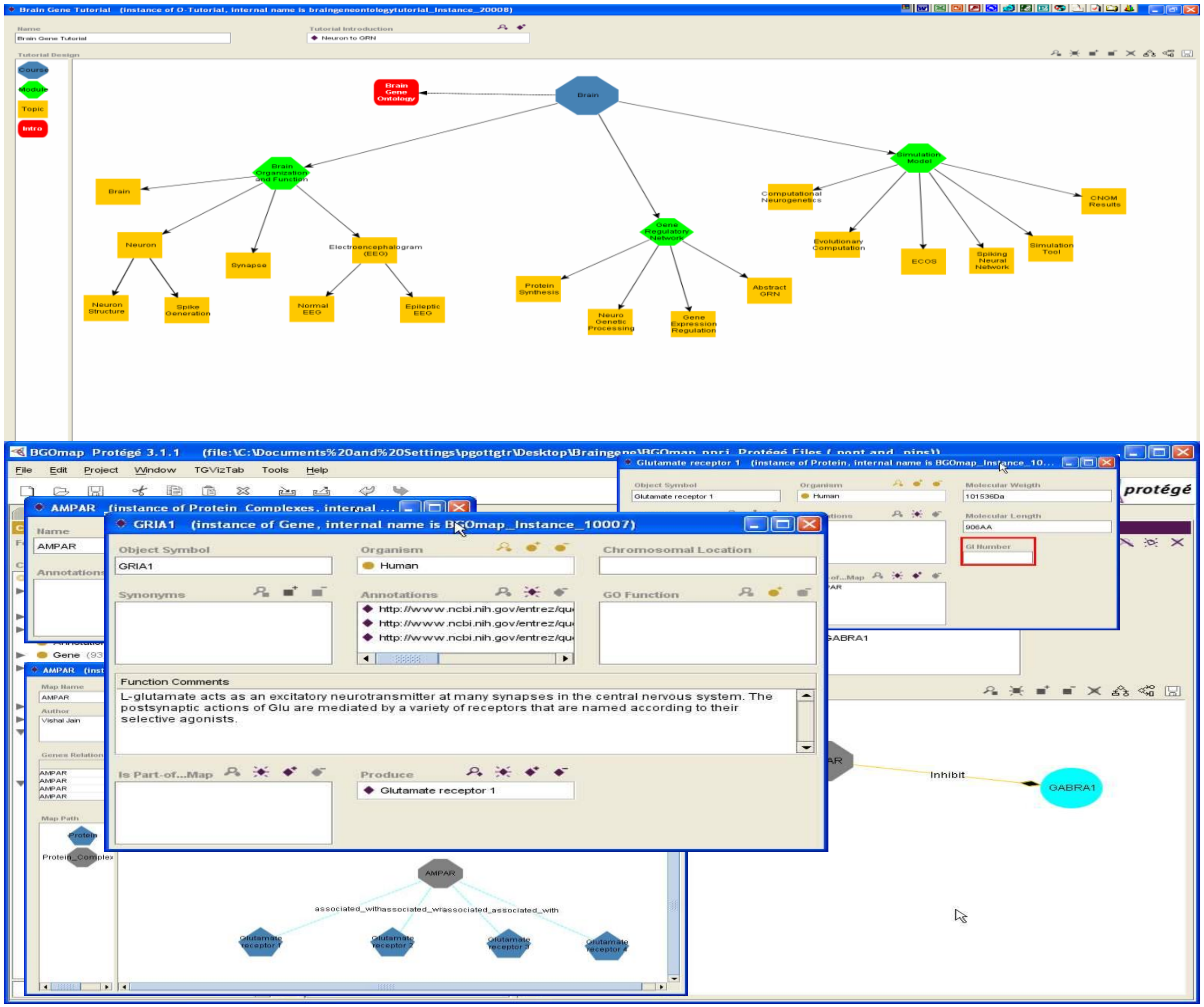
An integrated representation of all model variables and parameters to be optimised together.

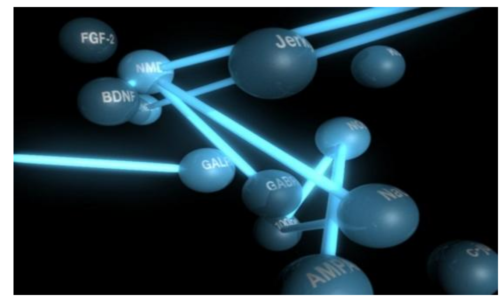
Work in progress: ngeSNN for modelling and understanding brain diseases

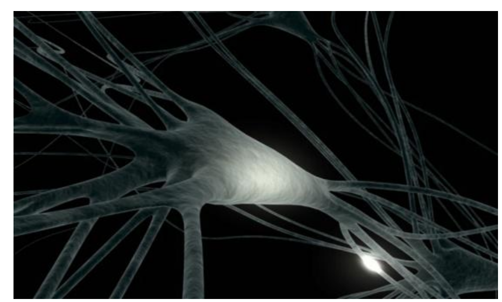
Table 1. Single and multiple genes related to some neurodegenerative diseases and brain abnormalities.

DISEASE	MUTATIONS OF GENES IDENTIFIED SO FAR	LOCATION OF GENES ON CHRO MOSOMES	BRAIN ABNORMALITY	SYMPTOMS	AGE OF ONSET
Alzheimer disease (AD)	PS2 (AD4) PS1 (AD3) unknown unknown	1 14 19 21	plaques made of fragmented brain cells surrounded by amyloid-family proteins, tangles of cytoskeleton filaments	progressive inability to remember facts and events and later to recognize friends and family	71 years
Amyotrophic lateral sclerosis (ALS)	SOD1 (codes for enzyme removing dangerous superoxide radicals)	21	progressive degeneration of motor neuron cells in the spinal cord and brain	loss of motor control which ultimately results in paralysis and death	between 55 and 75 years
Fragile X syndrome	FMR1 (codes for FMRI protein with unknown function)	X	failure of the glutamate synapse formation and elimination	the most common inherited form of mental retardation	1 year
Huntington disease (HD)	HD gene (codes for the protein huntingtin that stimulates expression of BDNF)	4	dilatation of ventricles and atrophy of caudate nucleus and striatum	degenerative neurological disease that leads to dementia	between 30 and 50 years
Rett syndrome	MeCP2 (codes for a protein which controls gene expression in the cell)	X	generalized brain atrophy, decrease in neuronal cell size, increased cell packing density, reduction in cholinergic neurons	loss of purposeful use of hands and speech, wringing hand movements, seizures, mental retardation	6 to 18 months
Williams syndrome	LIM kinase and elastin coding sequences	7	unknown	high competence in language, music and interpersonal relations, with low IQ	At birth

Work in progress: Integrated brain-gene ontology with ngeSNN. The KEDRI BGO (www.kedri.info)







6. Future SNN models and applications

- More efficient on-line learning algorithms for solving complex STP tasks, e.g. audio-visual, EEG, moving objects;
- Methods and algorithms for computation of FA of large number of states;
- Methods and algorithms for computation of AM of large number of patterns;
- Novel algorithms for CNGM;
- Medical decision support systems for personalised risk and outcome prediction of brain diseases: AD, Stroke, TBI;
- Neurogenetic robots;
- New hardware and software – reconfigurable software-hardware platforms;
- Large scale applications for cognitive systems;
- Large scale engineering applications , e.g.: cyber security, environmental disaster prediction, climate change prediction, ….

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

- Established June 2002
- Funded by AUT, FRST, NZ industry, projects with Japan and China.
- 4 senior research fellows and post-docs
- 25 PhD and Masters students;
- 25 associated researchers
- Both fundamental and applied research (theory + practice)
- 220 refereed publications
- 5 PCT patents
- Multicultural environment (9 ethnic origins)
- Strong national and international collaboration