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Neuroinformatics, Neural Networks and Neurocomputers for Brain-inspired AI: Evolvable and explainable Spatio-Temporal learning (STL)

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Director, Knowledge Engineering Ltd., https://knowledgeengineering.ai

Neuroinformatics, Neural networks and Neurocomputers: the premier *N3* (group) of science, technology and AI

Neuroinformatics offer a tremendous amount of data and knowledge about how the human brain and the nervous system work.

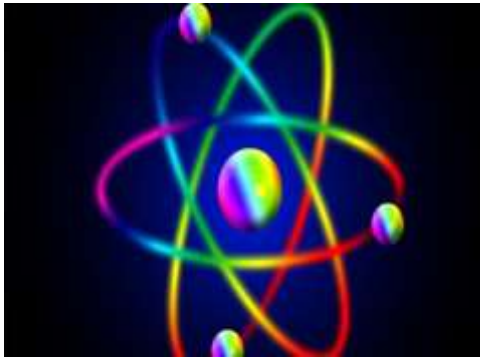
Many brain information processing principles can be now implemented in novel **Neural network** computational models.

The latter ones have inspired the development of neuromorphic hardware chips and N**eurocomputers,** characterised by much low power consumption, massive parallelism and fast processing.

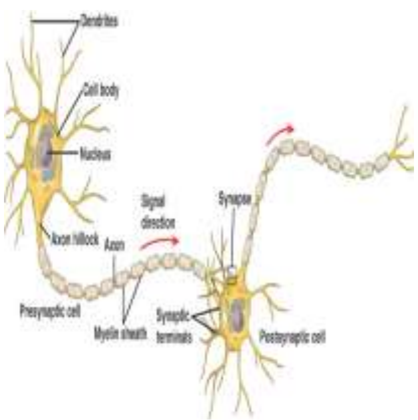
Evolvable and explainable spatio-temporal learning (STL): Learning systems that are structured according to a spatial or other relationship information of temporal data and are trained to evolve their structure by learning temporal associations of the data that are explainable.

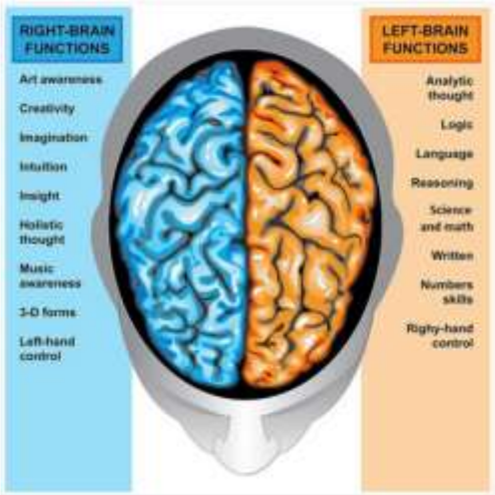
Content

1. Challenges in data science and AI and the need for evolving spatio-temporal learning (STL)







The most important systems and processes in Nature are evolvable spatio-temporal. How do we model and explain them?

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STL: Modelling the dynamics of space and time in a single model or ensembles of them?

Evolving ST processes in Nature:

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

“ Времето е в нас и ние сме във времето“

“Time lives inside us and we live inside Time.’

Vasil Levski-Apostola (1837-1873)
Bulgarian educator and revolutionary

Different types of spatio-temporal data (STD)

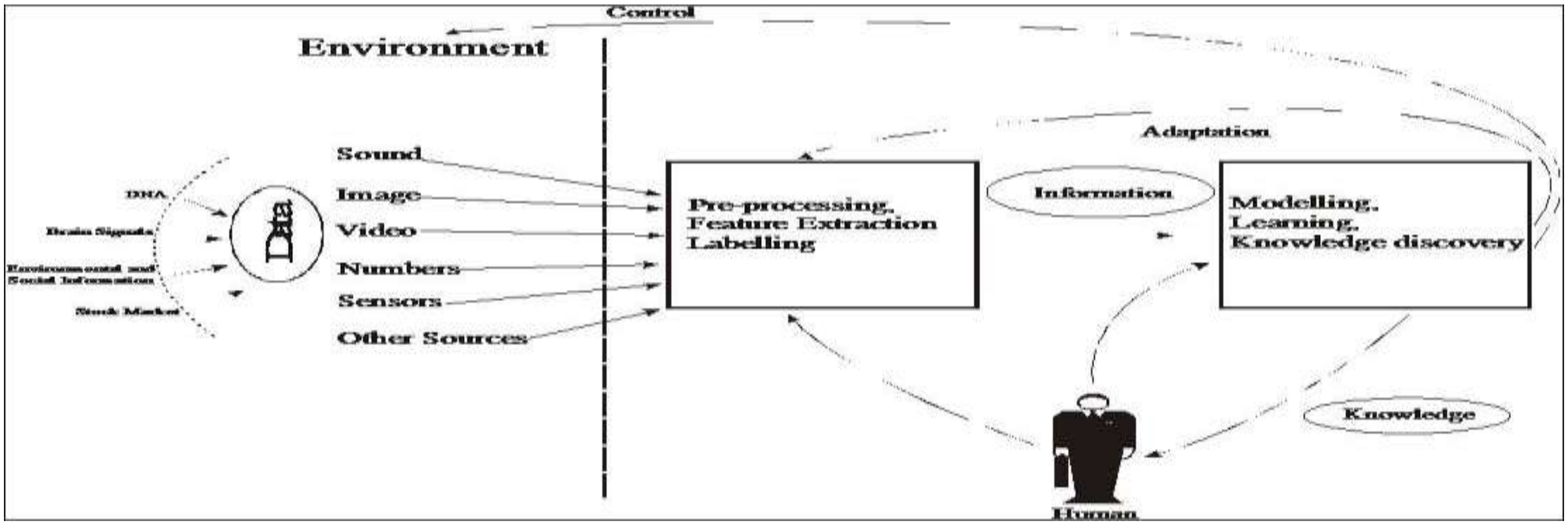
- Temporal (e.g. climate, financial data, gene expression)
- Spatio-temporal with fixed spatial location, (e.g. brain data; seismic; GPS)
- Spatio-temporal with changing locations of the spatial variables (e.g. moving objects)
- Spectro-temporal data (e.g. radio-astronomy; audio; speech; music)

Different characteristics of STD

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

The challenge: To better analyse, model and understand *STD* and the processes that generate these data and to predict future events in space and time.

Six challenges in data science and AI related to evolving spatio-temporal learning (STL)



1. Life-long STL
2. Personalisation of STL models.
3. Multiple modality STL (e.g. images, genetic, clinical, longitudinal, etc.)
4. Explainability in STL (extracting rules, associations) (explainable AI)
5. Human-machine symbiosis based on STL
6. Sustainability of AI

2. The human brain as the most sophisticated STL machine and the birth of BI-SNN

The brain (80bln neurons, 100 trillions of connections, 200 mln years of evolution) is the ultimate learning machine

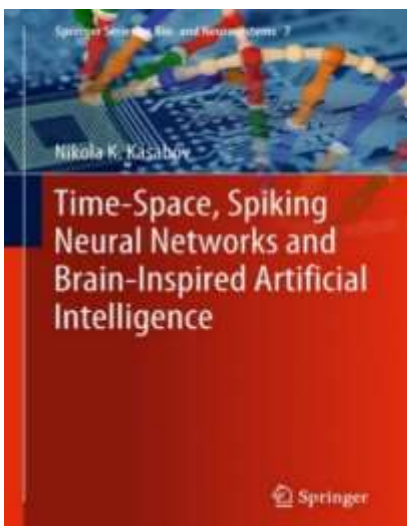
Three, mutually interacting, spatial memory types:

- short term (membrane potential);
- long term (synaptic weights);
- genetic (genes in the nuclei).

Temporal data at different time scales:

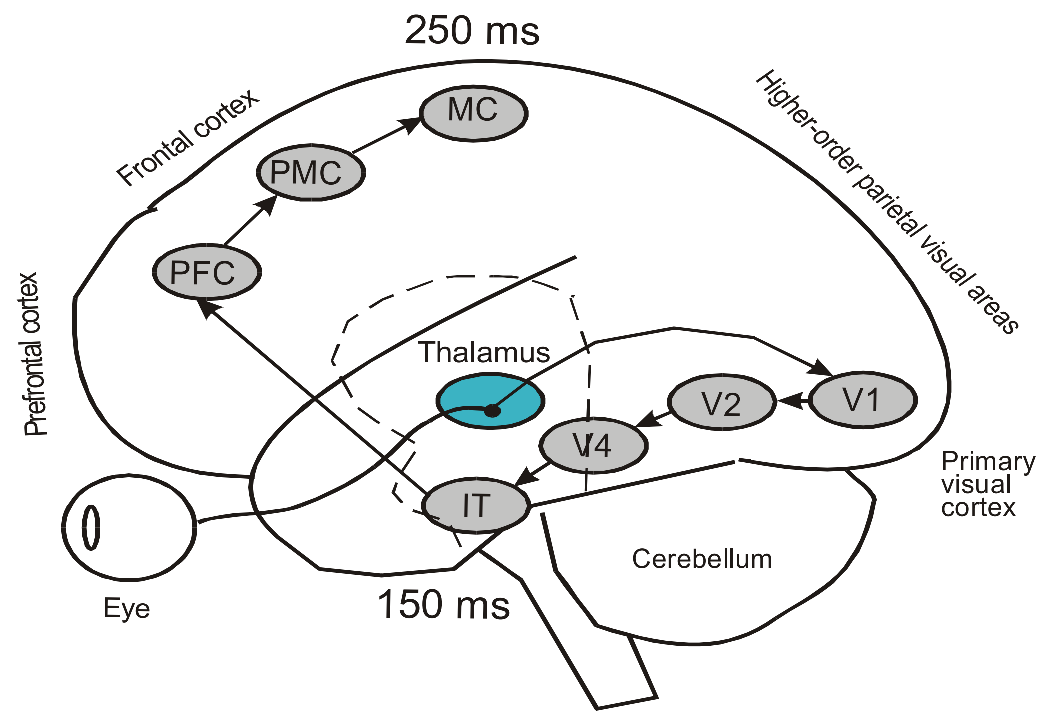
- Nanoseconds: quantum processes;
- Milliseconds: spiking activity;
- Minutes: gene expressions;
- Hours: learning in synapses;
- Many years: evolution of genes.

Knowledge is represented as deep **spatio-temporal patterns** that can evolve/adapt over time.



Kasabov, N., Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019), https://www.springer.com/gp/book/9783662577134

Knowledge of seeing an object and grasping it is learned incrementally as an **evolvable spatio-temporal trajectory** of connections between clusters of neurons in the brain

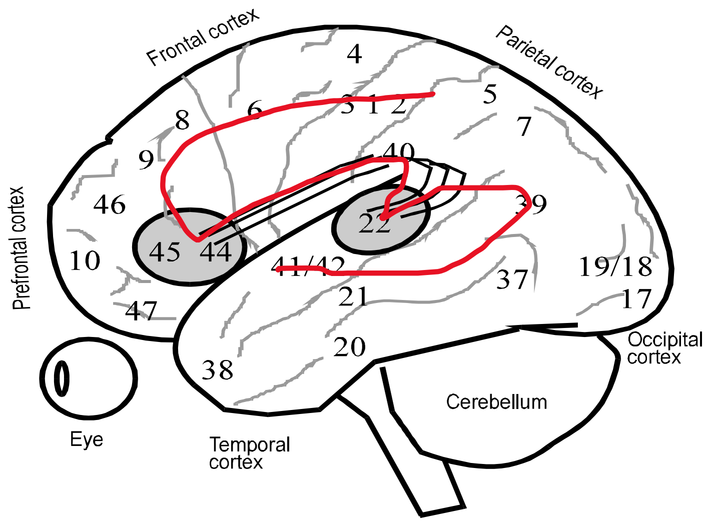


Deep serial processing of visual stimuli in humans for image classification and action.

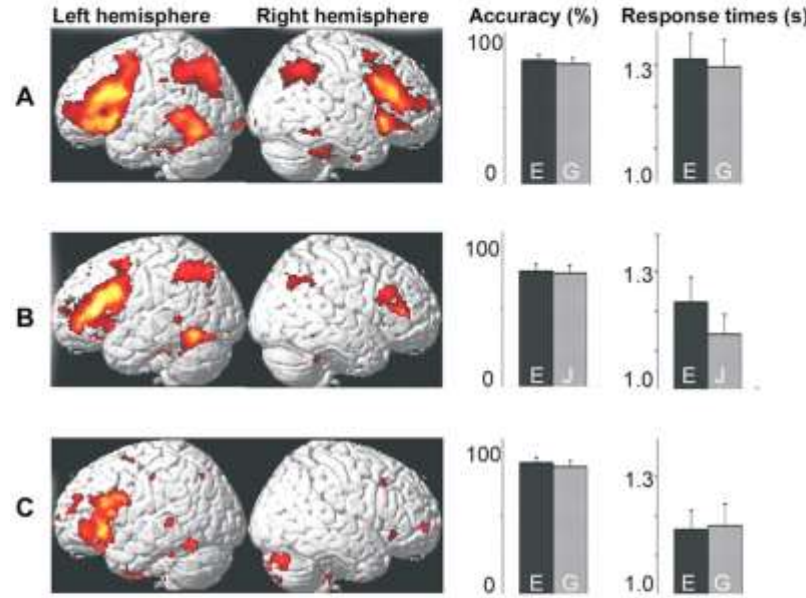
Location of cortical areas: V1 = primary visual cortex, V2 = secondary visual cortex, V4 = quartiary visual cortex, IT = inferotemporal cortex, PFC = prefrontal cortex, PMC = premotor cortex, MC = motor cortex.

L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer, 2007

STL of speech and language



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

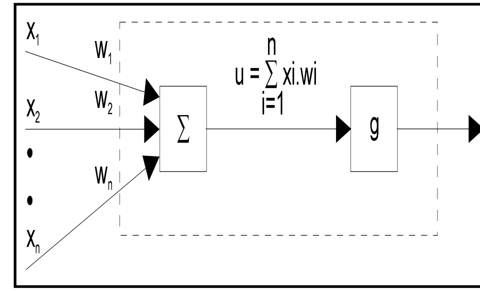


Common brain activation areas in bilingual subjects (Crinion et al, Science, 2006)

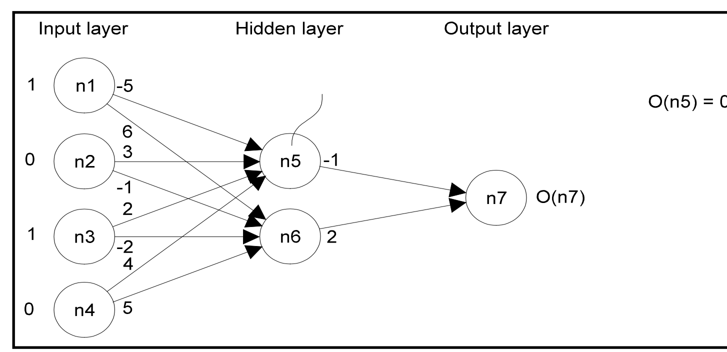
The basic model of language processing during the simple task of repeating the word that has been heard is the Wernicke-Geschwind model (Mayeux and Kandel 1991). A language task involves transfer of information from the inner ear through the auditory nucleus in thalamus to the primary auditory cortex (Brodmann's area 41), then to the higher-order auditory cortex (area 42), before it is relayed to the angular gyrus (area 39). From here, the information is projected to Wernicke's area (area 22) and then, by means of the *arcuate fasciculus*, to Broca's area (44, 45), where the perception of language is translated into the grammatical structure of a phrase and where the memory for word articulation is stored. This information about the sound pattern of the phrase is then relayed to the facial area of the motor cortex that controls articulation so that the word can be spoken.

The beginning to address of AI challenges:
Celebrating 80 Years of Neural Networks

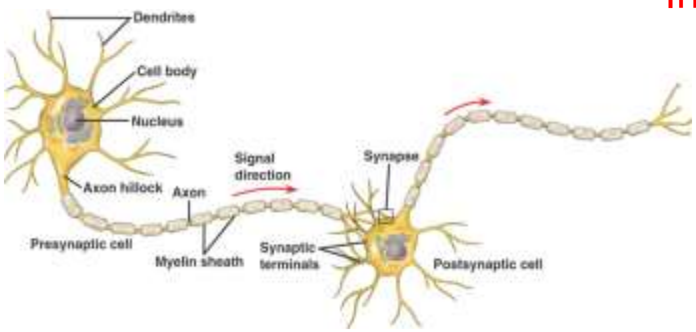
- ANN are computational models that mimic the nervous system in its main function of adaptive learning and *generalisation.*
- ANN as learning *models*
- 1943, McCulloch and Pitts neuron
- 1962, Rosenblatt - Perceptron
- 1971- 1986, Amari, Rumelhart, Werbos- Multilayer perceptron
- S.Grossberg and Carpenter (ART), Kohonen (SOM), W.Freeman, J.Taylor, …
- Many engineering applications.

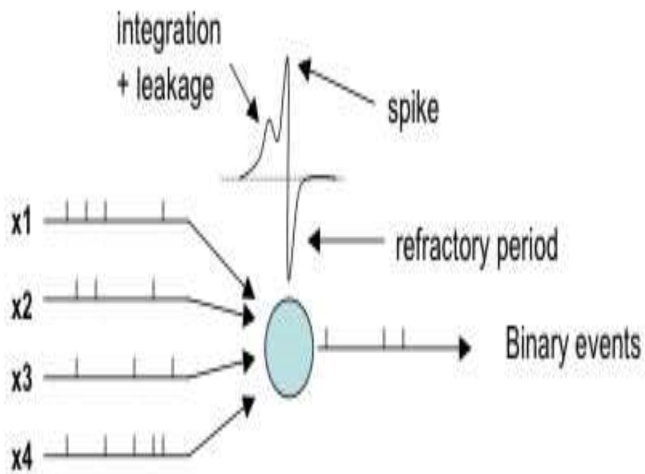


- Early NN were 'black boxes' and also - once trained, difficult to adapt to new data without much 'forgetting'.

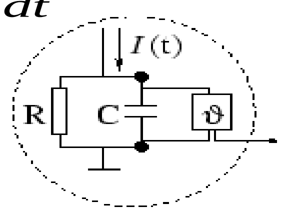


Spiking Neural Networks (SNN) can capture incrementally time and space





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



Information processing principles in neurons and neural networks:

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

Spiking neural networks (SNN)

- Leaky Integrate-and-fire
- Probabilistic model
- Neurogenetic model

They offer the potential for:

- Spatio-temporal data processing
- Bridging higher level functions and “lower” level genetics
- Integration of modalities

SNN open the field of brain-inspired (cognitive, neuromorphic) computing.

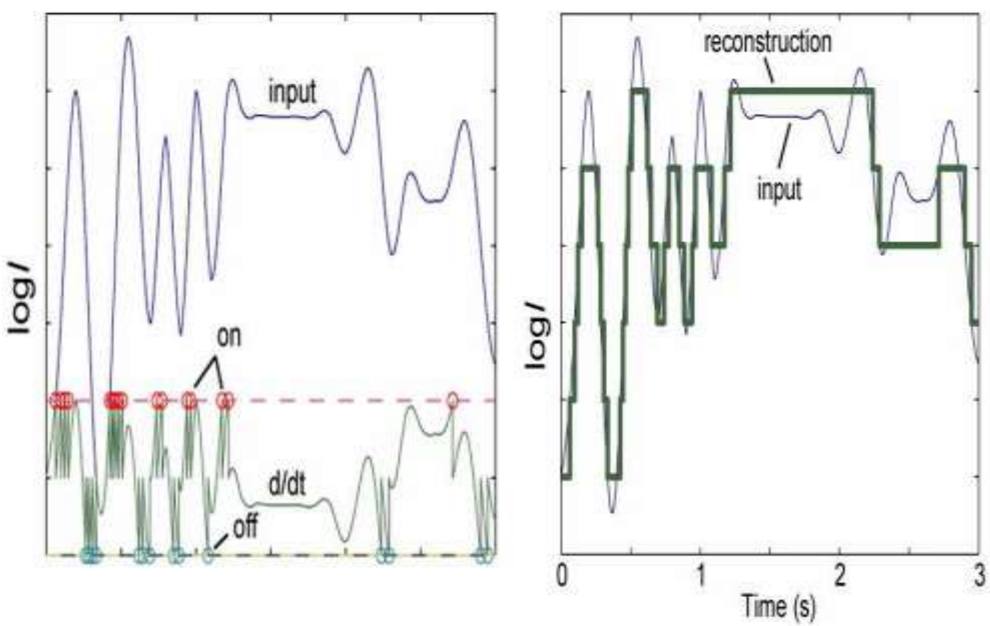
“*The goal of brain-inspired computing is to deliver a scalable neural network substrate while approaching fundamental limits of time, space, and energy,*” IBM Fellow **Dharmendra Modha**, chief scientist of Brain-inspired Computing at IBM Research,

Spike encoding methods for STL

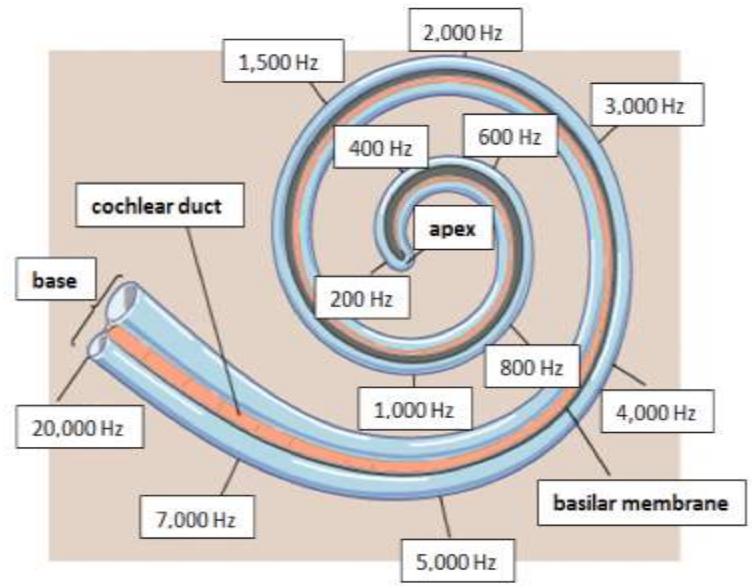
A spike is generated only if a change in the input data occurs beyond a threshold

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

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



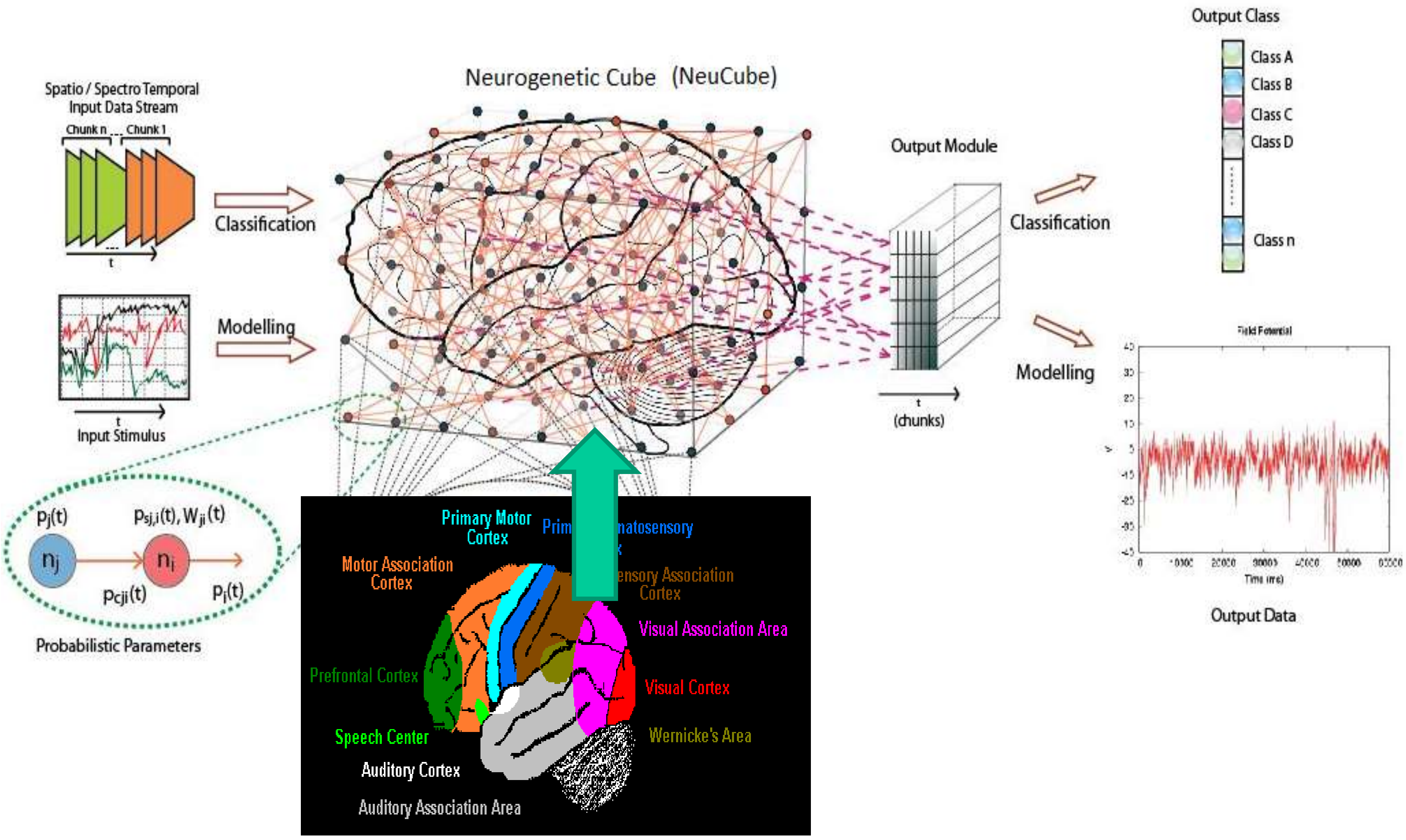
Threshold-based encoding – retinotopic mapping for spatio-temporal data



Tonotopic organization of the cochlea for spectro-temporal data

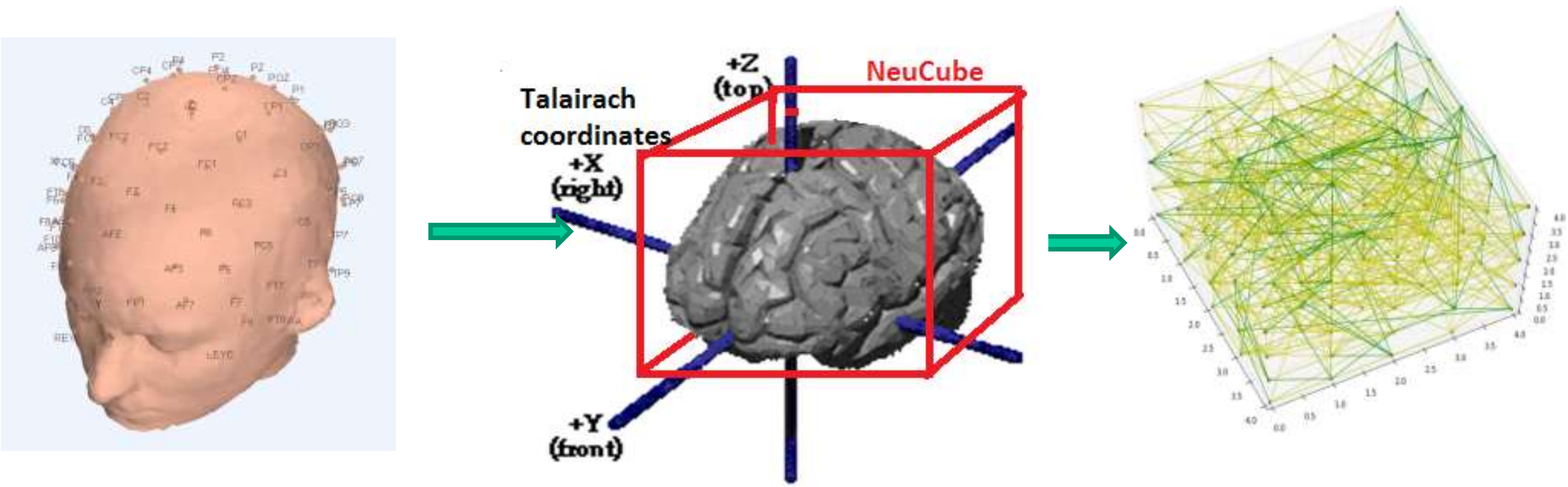
https://sites.google.com/site/jayanthinyswebite

4D BI-SNN: The NeuCube Architecture for STL (3D space + 1D time)



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

Spatio-temporal mapping of brain data into a 4D SNNcube for STL



Further development of ideas from SOM (Kohonen) and ART (Grossberg)

E. Tu, N. Kasabov, J. Yang, Mapping Temporal Variables into the NeuCube Spiking Neural Network Architecture for Improved Pattern Recognition and Predictive Modelling, IEEE Trans. on Neural Networks and Learning Systems, 28 (6), 1305-1317,, 2017 DOI: 10.1109/TNNLS.2016.2536742, 2017.

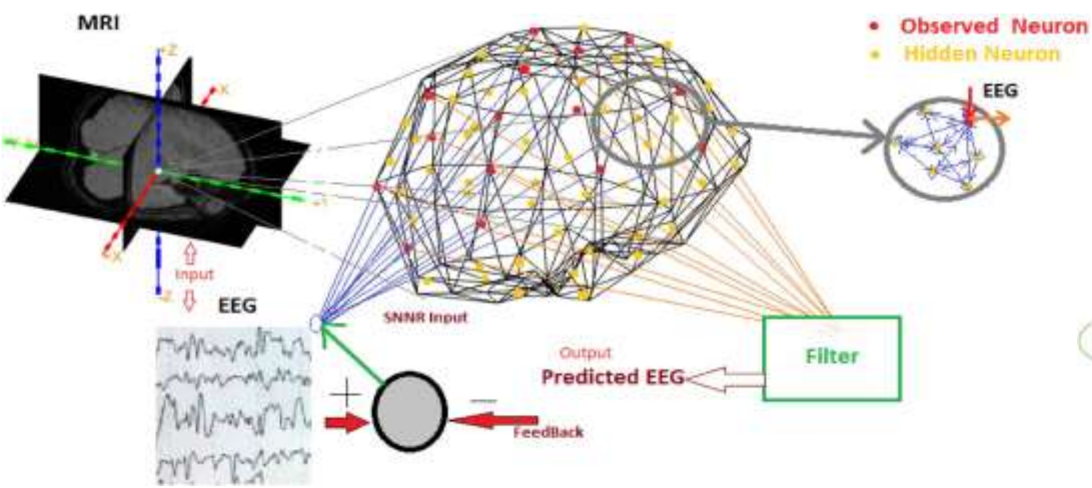
Different templates can be used to **spatially structure** a SNN to enable STL

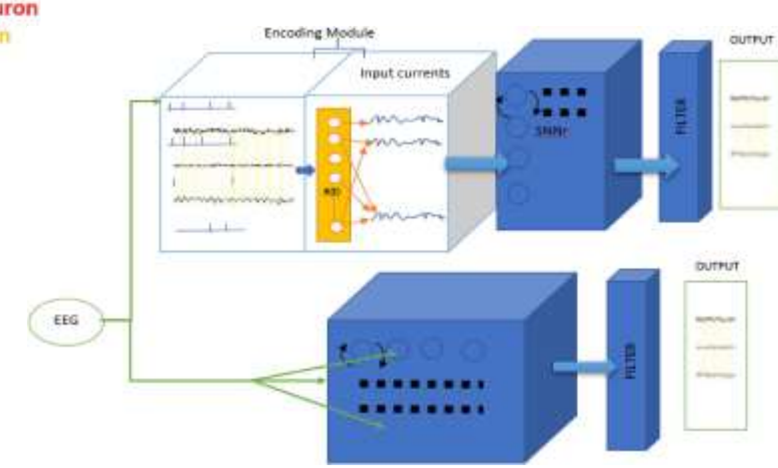
Spatial templates (e.g. brain Talairach, MNI, MRI, etc.; geographical maps; molecular structure; quantum)

Temporal aspect - Learning: Using encoded vs real value signals

Example: Personalised MRI structured BI-SNN and learning algorithms for personalized modelling, analysis, and prediction of EEG signals, S Saeedinia, MJahed-Motlagh, ATafakhori & N Kasabov, *Scientific Reports,* **11**,12064 (2021)

Training the SNN to predict the signals on the input neurons → As a result of the spatial location of the neurons, all of them can also predict their spiking activities!!

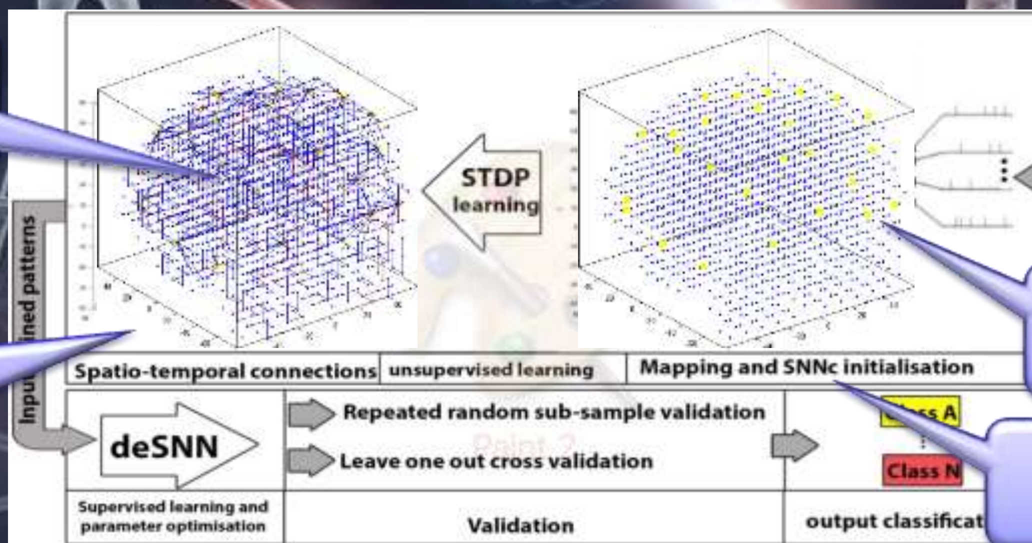




eSTL in NeuCube

Creation of Neuron Connections During The Learning

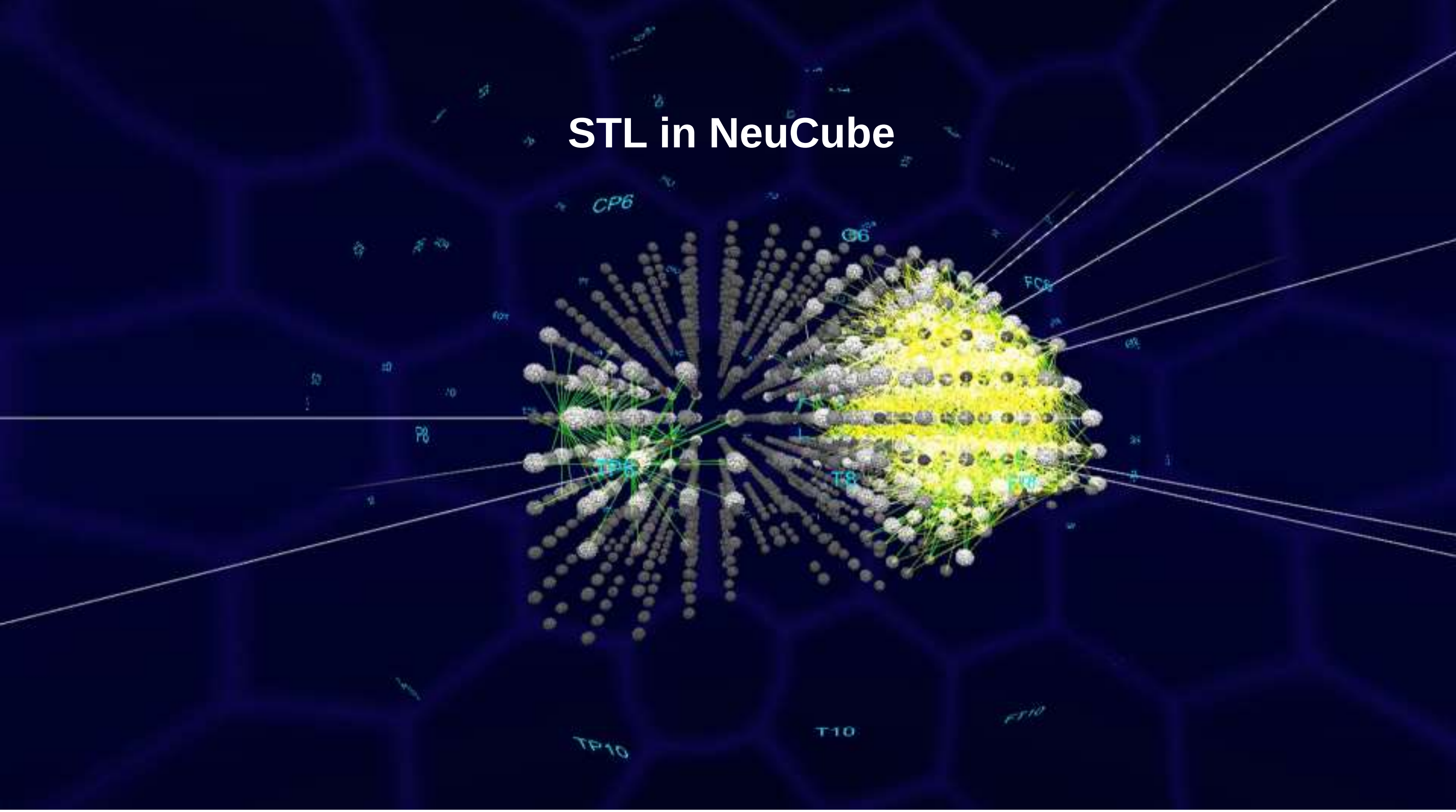
The More Spike Transmission, The More Connections Created



Spike Trains Entered to the SNNc

Neuron Spiking Activity During the STDP Learning

STL in NeuCube



N. Kasabov, N. Scott, E.Tu, S. Marks, N.Sengupta, E.Capecci, M.Othman,M. Doborjeh, N.Murli,R.Hartono, J.Espinosa-Ramos, L.Zhou, F.Alvi, G.Wang, D.Taylor, V. Feigin,S. Gulyaev, M.Mahmoudh, Z-G.Hou, J.Yang, Design methodology and selected applications of evolving spatio- temporal data machines in the NeuCube neuromorphic framework, Neural Networks, v.78, 1-14, 2016. http://dx.doi.org/10.1016/j.neunet.2015.09.011.

Life-long STL

- How is life-long STL performed in the brain?

D Kudithipudi et al H.Siegelman, Biological underpinnings for lifelong learning machines, NatMI, vol.4,2022

Neurogenesis
Neuromodulation
Episodic replay
Metaplasticity
Multisensory integration

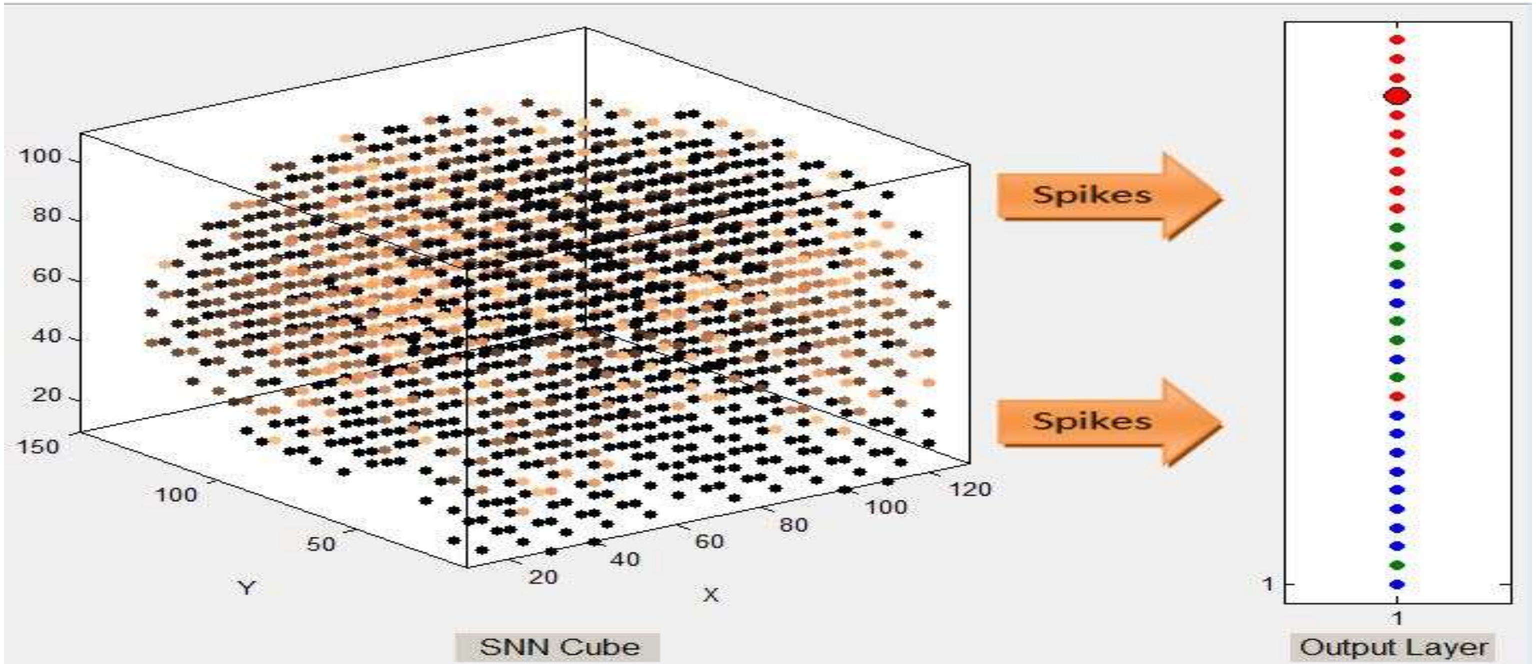
- How life-long STL can be achieved in ANN?

G.I. Parisi, R.Kemker, J. L. Part, C. Kanan, S.Wermter, Continual lifelong learning with neural networks: A review, Neural Networks, 113, 2019, 54-71

- How can life-long be implemented in BI-SNN?

Spike-frequency or spike-time predictive modelling at single neurons using error backpropagation
Neuromodulatory synaptic connection
Weight regulation
Homeostasis
Lyapunov energy function
Evolving classifiers/regressors (deSNN) where neuronal outputs are evolved and aggregated continuously

Extracting fuzzy spatio-temporal rules from STL models



Example of TSR representation in a trained SNN classifier

IF (area (Xi,Yi,Zi) in the Cube with a cluster radius Ri is activated at time about T1) AND

(area (Xj,Yj,Zj) with a cluster radius Rj is activated at time about T2) AND

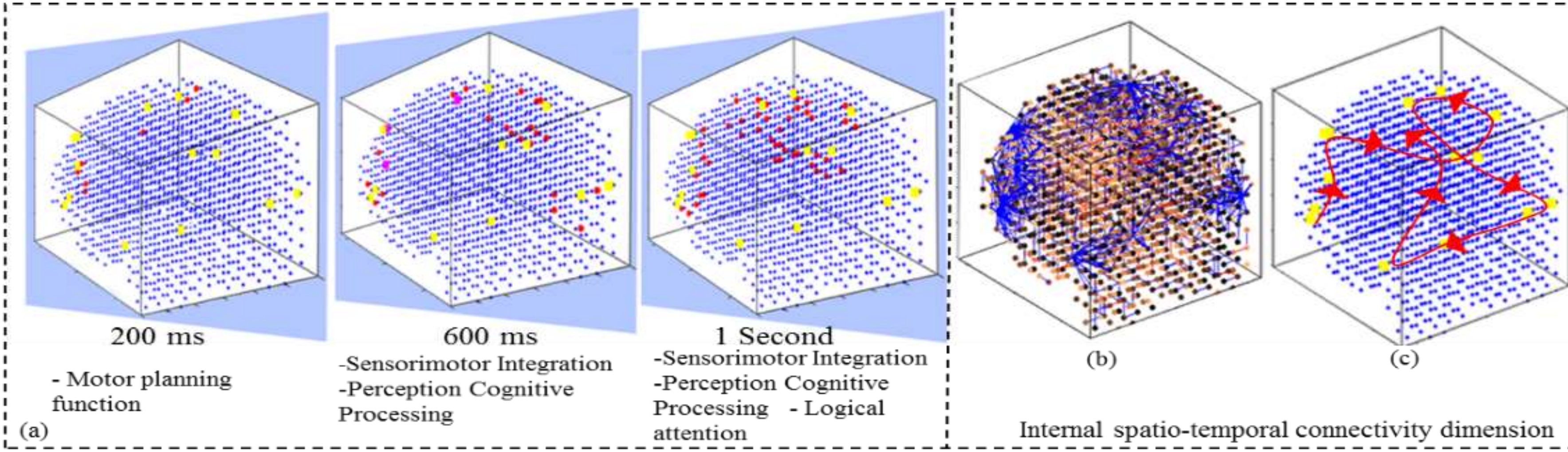
(area (Xk,Yk,Zk) with a cluster radius Rk is activated at time about T3) AND

(no other areas of the SNNcube are activated)

THEN (The output class prototype is number 4 from class 1).

STL in NeuCube represented as a spatio-temporal trajectory and a spatio-temporal fuzzy rule

A SNNcube that learns EEG data from 14 EEG channels when a person is moving a wrist. The sequence of connections of the trained SNNcube can be interpreted as TSR. The figure is showing only few aggregated events (out of 1000, one at each millisecond EEG data).



TSR representation of time and space aggregated events:

IF (a person is moving a hand up)

THEN (the following brain functions are activated in space and time):

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

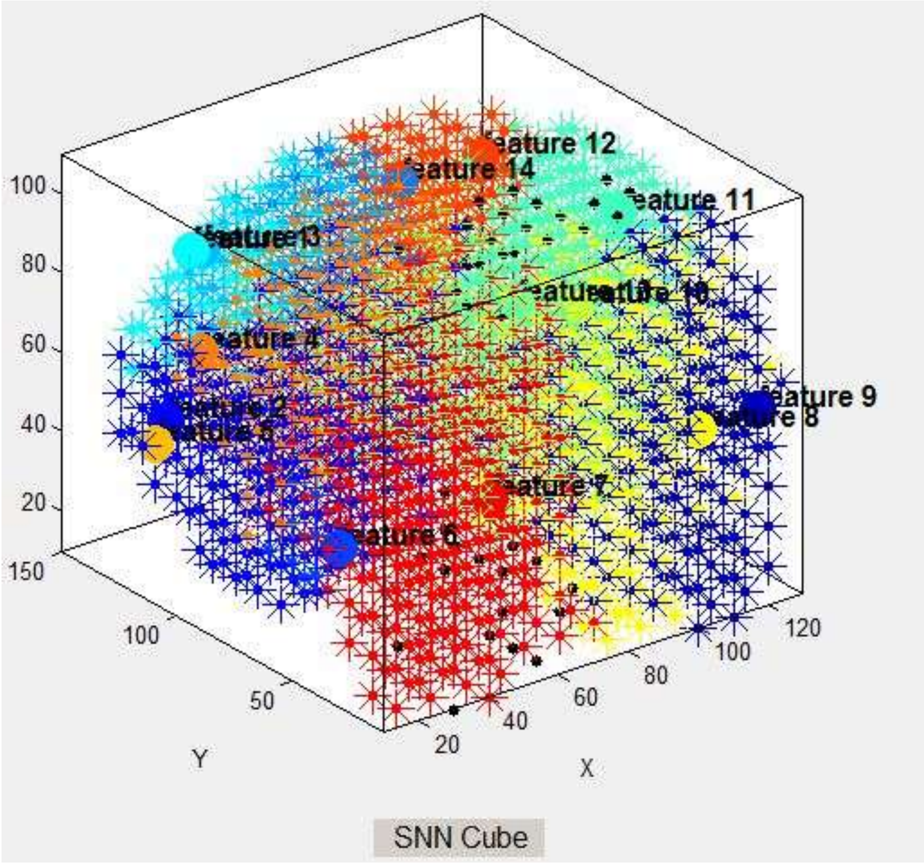
AND E2: Sensorimotor integration, in the Sensorimotor integration brain area, at time T2

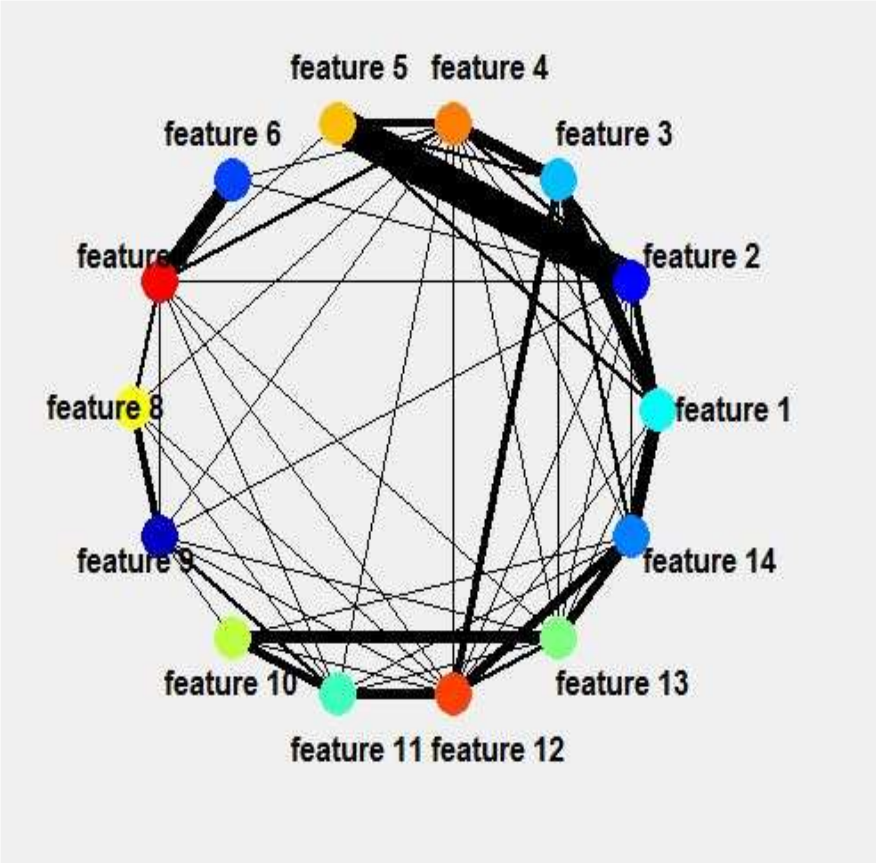
AND E3: Perception, in the Perception Cognitive brain area, time T3

AND E4: Attention, in the Logical Attention brain area, time T4.

Evolving spatio-temporal graphs as representation of STL

- Clusters of highly connected neurons to input neurons;
- Clusters of spiking activity spread from input neurons ;
- A dynamic graph of information exchange between spatially distributed clusters around the inputs (Feature Interaction networks)





Manifesting the benefits of STL on brain data:

- evolvability (on-line learning)
explainability
- higher accuracy on brain EEG personal data

P.Koprinkova-Hristova, D.Penkov, S.Georgiva, L. Ivanov, N.Kasabov, On-line Learning, Classification and Interpretation of Brain Signals using 3D SNN and ESN, IJCNN'23, paper 1570886886

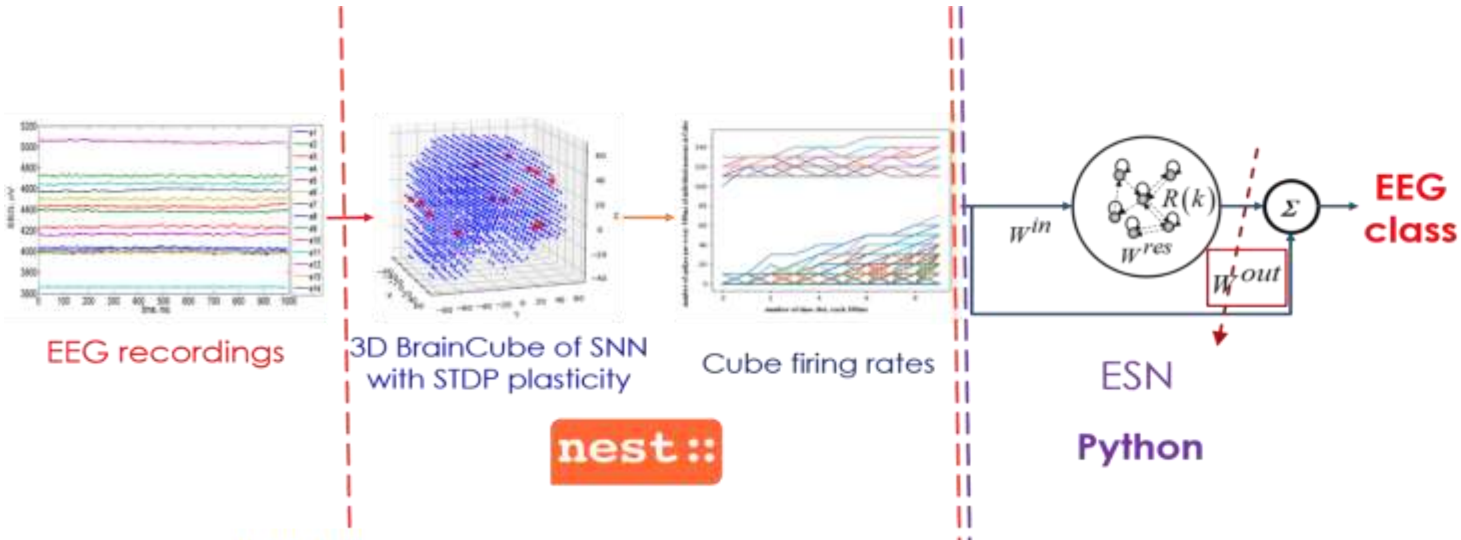


TABLE II

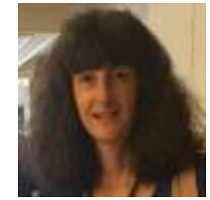
MINIMUM TEST ERROR FOR EACH SIZE OF THE ESN RESERVOIR AND BEST SNN PARAMETERS

M	sp	a	s_{in}	s_{out}	MSE_{test}
3000	0.7	0.4	1e-5	1e-5	1.589e-05
3500	0.7	0.6	1e-3	1e-2	1.358e-05
4000	0.6	0.4	1e-4	1e-2	1.590e-05
4500	0.7	0.4	1e-3	1e-5	1.360e-05
5000	0.6	0.4	1e-5	1e-2	1.292e-05

TABLE III

IUM TEST ERROR FOR EACH SIZE OF THE ESN RESERVOIR WITHOUT THE SNN PRE-PROCESSING

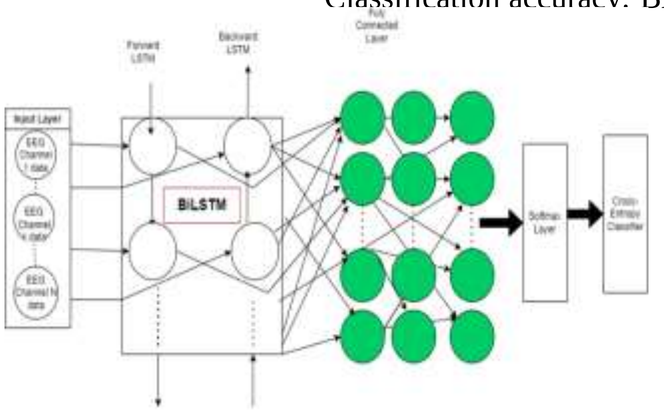
M	sp	a	s_{in}	s_{out}	MSE_{test}
3000	0.4	0.7	1e-5	1e-2	0.013
3500	0.4	0.5	1e-5	1e-1	0.015
4000	0.4	0.5	1e-5	1e-5	0.011
4500	0.7	0.5	1e-5	1e-2	0.013
5000	0.7	0.4	1e-3	1e-2	0.018

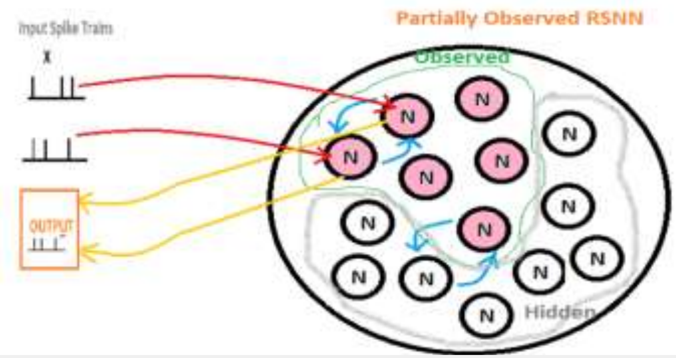


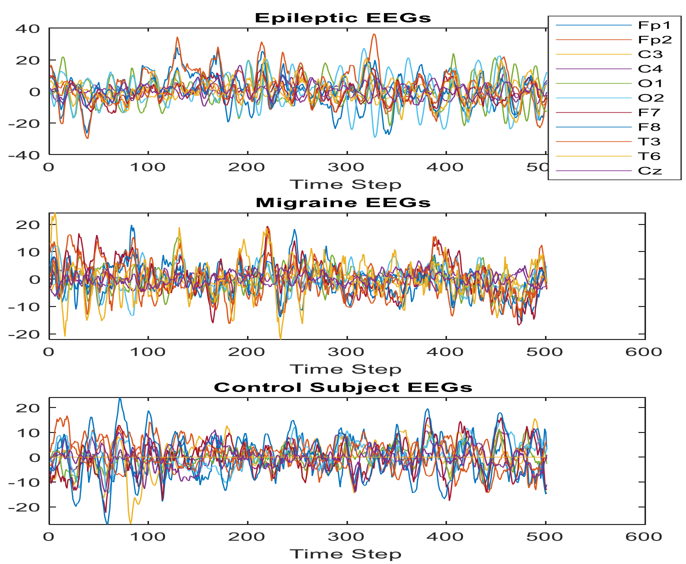
Higher classification accuracy of multiple subject brain EEG data and biomarker discovery using STL

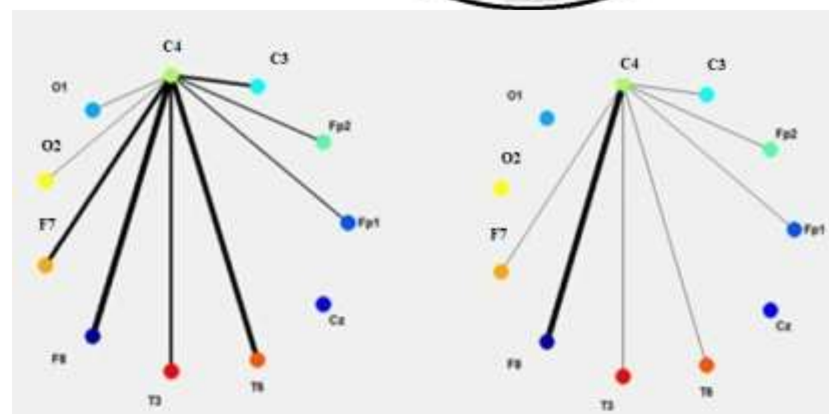
S. Saeedinia, M.Reza Jahed- Motlagh, A. Tafakhori, N. K. Kasabov, Diagnostic biomarker discovery from brain EEG data with LSTM, reservoir-SNN and NeuCube: Methods and a pilot study on epilepsy vs migraine, submitted IEEE Tr PAMI, IEEE archive, https://www.techrxiv.org/, June 2023.

Classification accuracy: BiLSTM: 90%; RSNN: 85%; NeuCube: 97%









a) 3 Classes- EEG biomarkers

b) 2 Classes- EEG biomarkers

3. Personalisation of STL models

Personalised predictive modelling of individual risk of stroke

How environmental risk factors can influence the risk of individual stroke occurrence?

>1200 individuals

Stroke (2011-2012)

Clinical records (37 variables)

Affected group of 169 individuals: (45% female); 55% male; mean-age= 74.05> mean-age non-affected group (70.4); had *history of stroke* in close family member, *overweight*, *older*, *smokers*, *diabetic*, and taking *medication*.

10 environmental (CO, NO2, O3, SO2, and PM10, PM2.5, temperature, wind-direction average, wind-speed, and solar radiation).

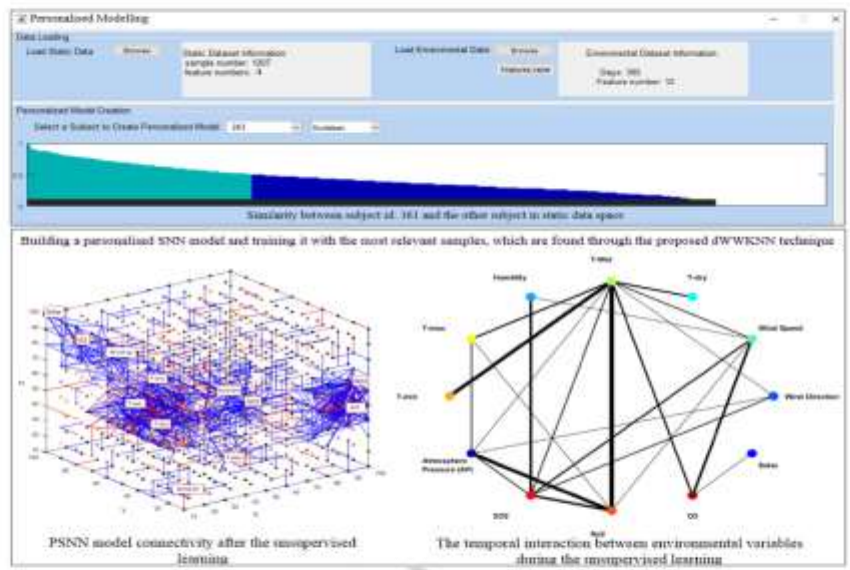


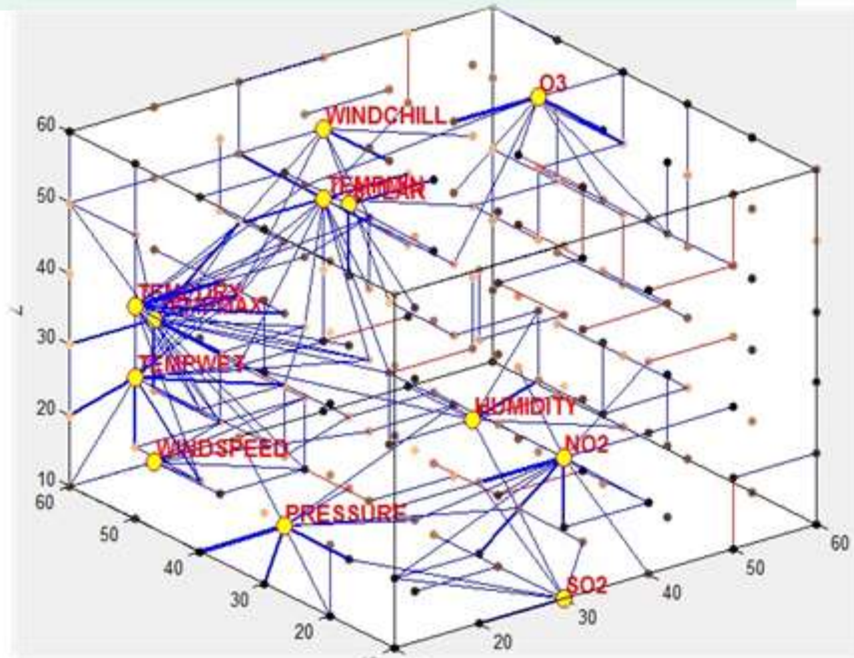
Fig. 9. The user interface of the proposed personalised predictive system for prediction of risk of stroke. A PSNN model is created to spatially map the environmental variables, where the most correlated variables are mapped to closer input neurons. Then the PSNN model was trained on the temporal spike sequences using STDP unsupervised learning to adapt the model connections. Blue lines represent excitatory synapses (positive connections), whereas red lines refer to inhibitory synapses (negative connections). In the graph, the amount of spike communication between clusters of neurons, centred by input variables, is captured as the thickness of lines. The thicker the line, the more interactions between variables during STDP learning.

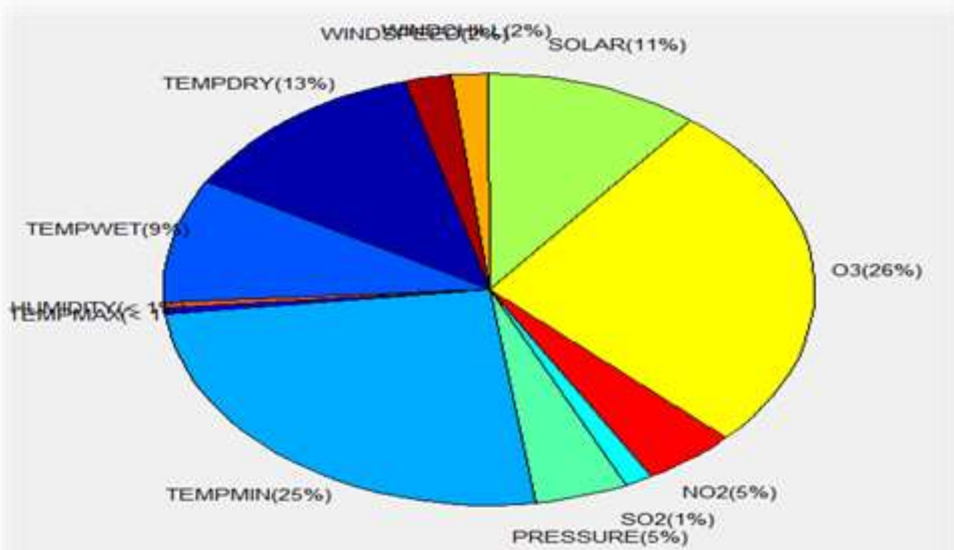
Maryam Doborjeh, Zohreh Doborjeh, Alexander Merkin, Rita Krishnamurthi, Reza Enayatollahi, Valery Feigin, **Nikola Kasabov**, Personalised Spiking Neural Network Models of Clinical and Environmental Factors to Predict Stroke, Cognitive Computation, COGN-D-20-00511R2, 26 , 2021, https://www.springer.com/journal/12559.

Personalised prediction of risk for stroke days ahead

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

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



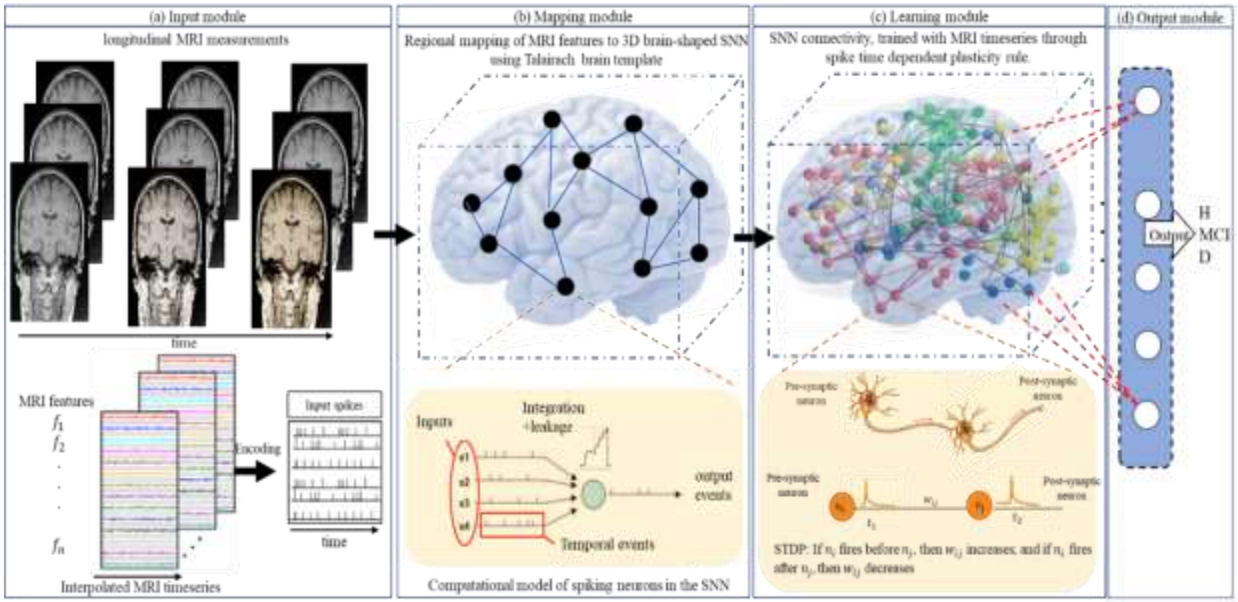


(d) Neuron proportion based on spike transmission

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

STL for personalised prediction of dementia using longitudinal MRI data and NeuCube

M. Doborjeh, Z.Doborjeh, A.Merkin, H.Bahrami, A.Sumich, R.Krishnamurthi, O. Medvedev, M.Crook-Rumsey, C. Morgan, I.Kirk, P.Sachdev, H. Brodaty, K. Kang, W.Wen, V. Feigin, N. Kasabov, Personalised Predictive Modelling with Spiking Neural Networks of Longitudinal MRI Neuroimaging Cohort and the Case Study ofr Dementia, Neural Networks, vol.144, Dec.2021, 522-539, https://doi.org/10.1016/j.neunet.2021.09.013,



	BiLSTM Accuracy	BiLSTM F-Score	NeuCube Accuracy	NeuCube F-Score
Classification	43%	56%	95%	94%
2-year ahead prediction	40%	40%	91%	89%
4-year ahead prediction	41%	46%	73%	67%

PM based on ECOS and NeuCube result in a better diagnostic and prognostic accuracy and a better explanation

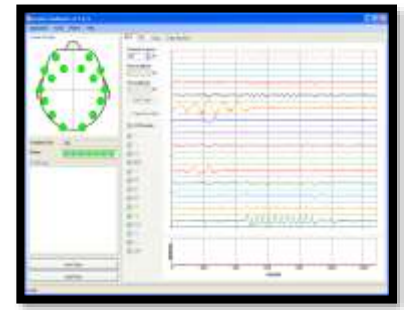
Example Applications	PM	Other AI methods accuracy
Schizophrenia Predicting formal diagnosis in next six months using gene expression measures from blood test	98%	92-97.5%
Mindfulness Treatment Predicting response to depression treatment using EEG data	73%	48.5-58.5%
Methadone Predicting treatment programme outcome using EEG data	91%	60-63%
Stroke Predicting stroke events using patient and environmental data	94%	67.5-87.5%
AD/MCI/normal Prediction 2 years ahead	91%	40% (LSTM)
Knee pain prediction 12 months after surgery using only pre-operative data	92%	66%

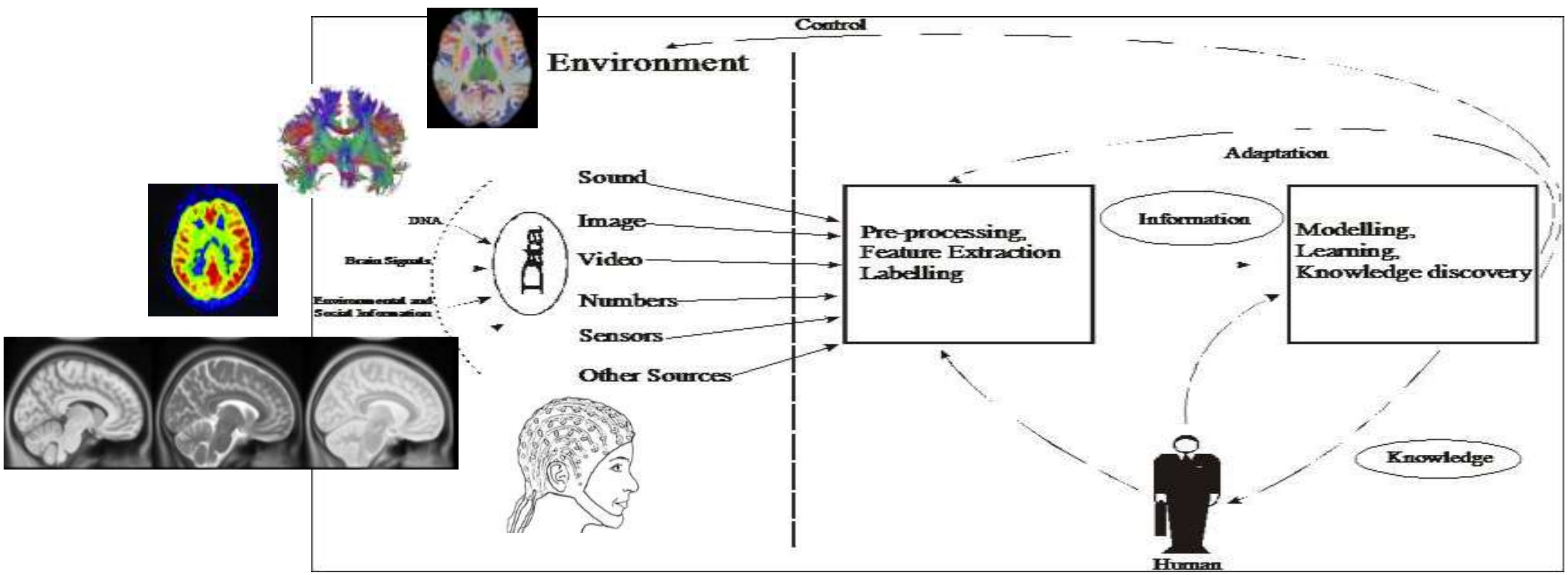
KNOWLEDGE ENGINEERING & DISCOVERY RESEARCH INSTITUTE

AN INSTITUTE OF AUT UNIVERSITY

4. STL for multiple modality data

- different spatial scales
- different time scales





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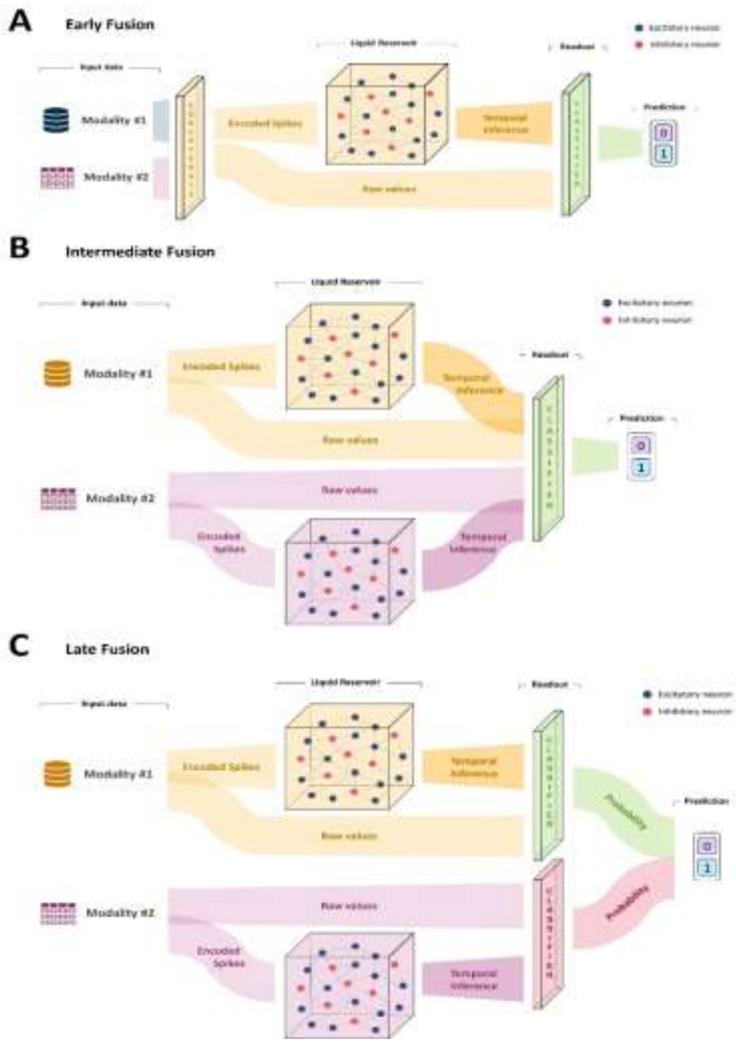
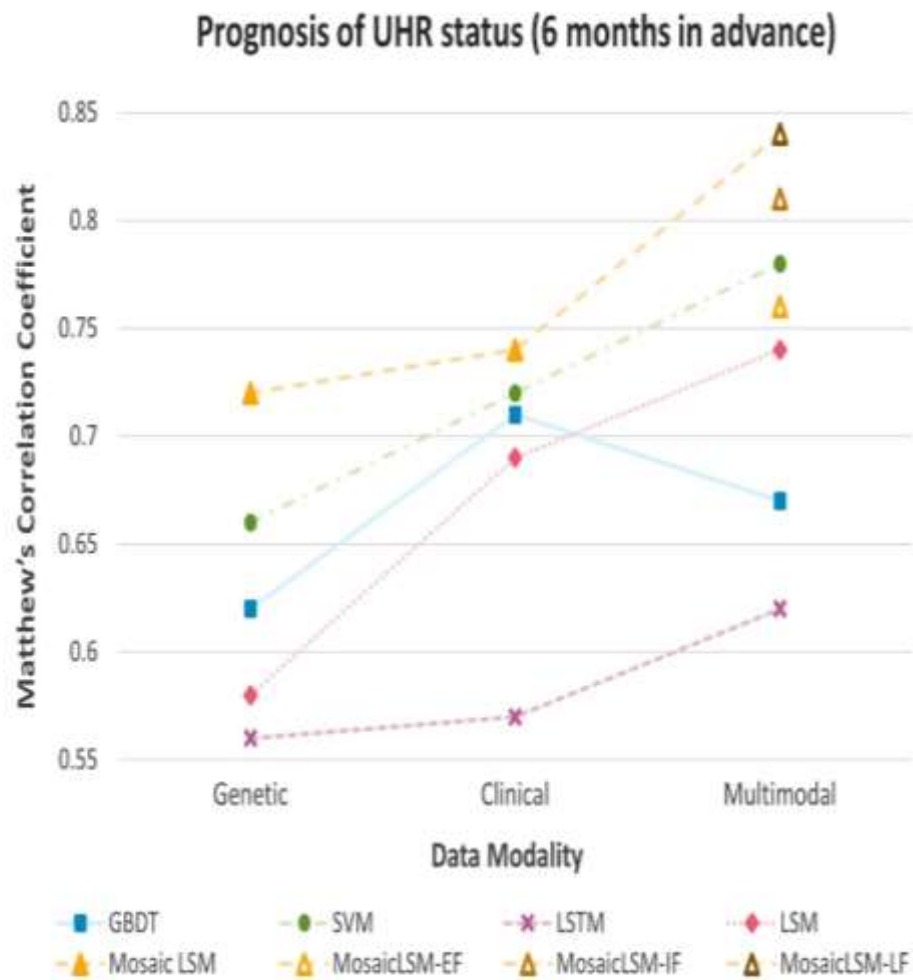
Early-, intermediate- and late longitudinal data fusion

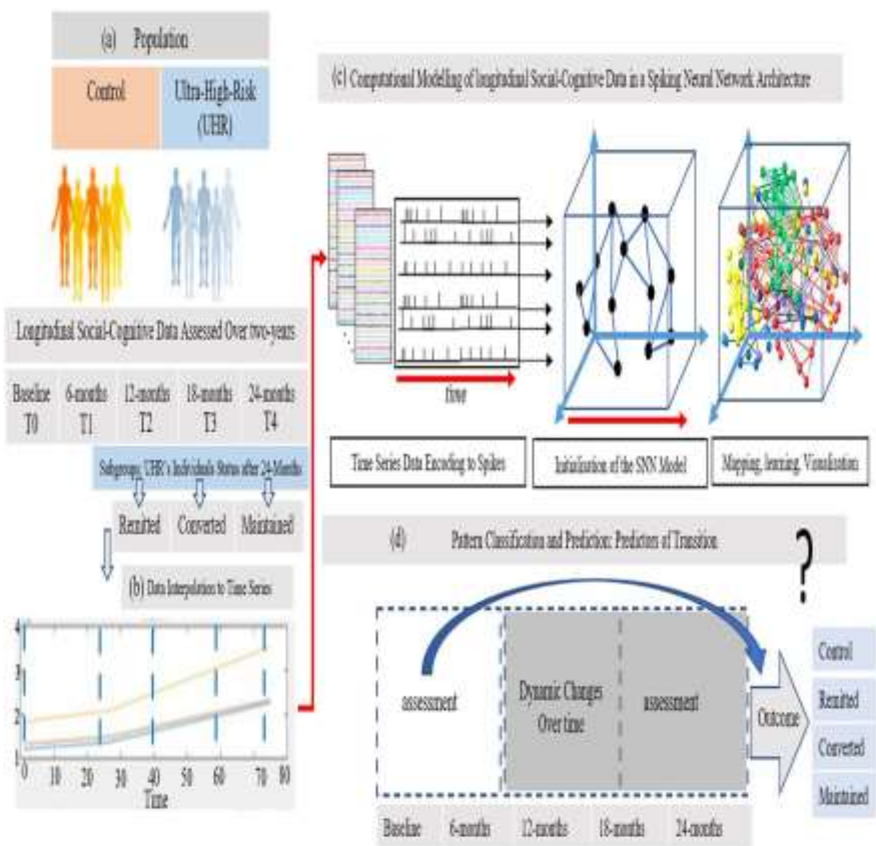
Sugam Budhraja, B.Singh, S.Tan, M.Dobrojeh, Z.Doborjeh, W.Goh, E.Lai and N.Kasabov, Mosaic LSM: A Liquid State Machine Approach for Multimodal Longitudinal Data Analysis, IJCNN 2023, paper 1570886977

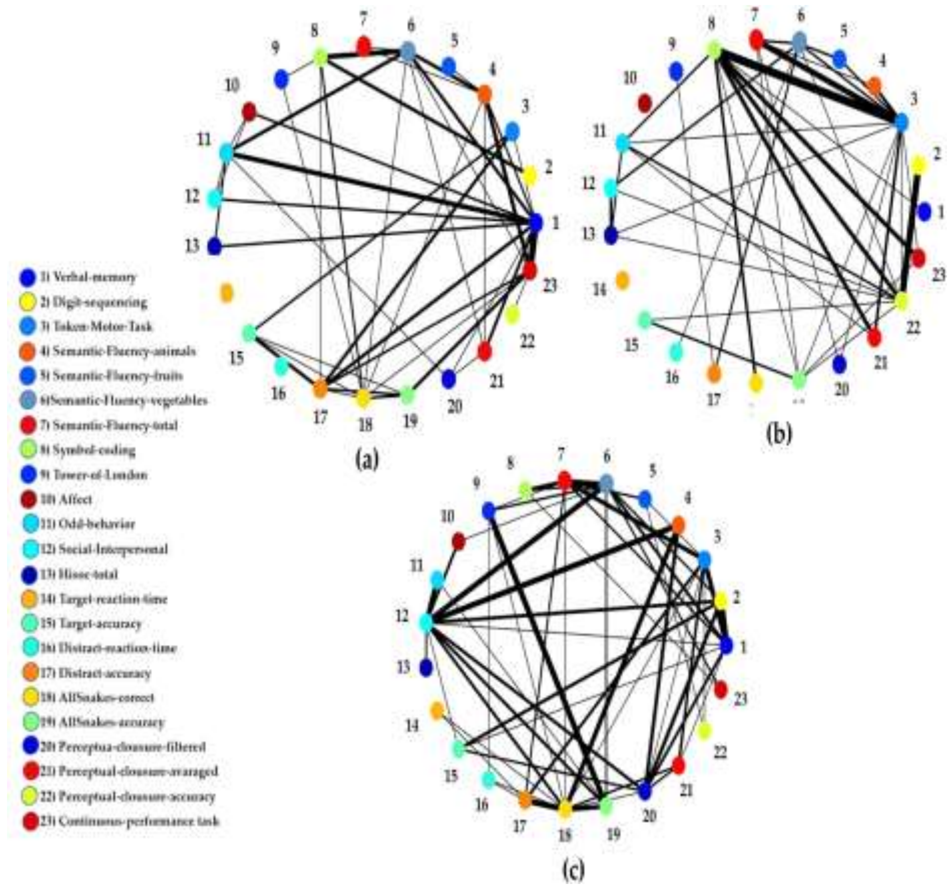




Integrating social and cognitive longitudinal data for predicting psychosis

Zohreh Doborjeh, Maryam Doborjeh, Alexander Sumich, Balkaran Singh, Alexander Merkin, Sugam Budhraja, Wilson Wen Bin Goh, Edmund Lai, Margaret Williams, Samuel Tan, Jimmy Lee, and Nikola Kasabov, Investigation of Social and Cognitive Predictors in Non-Transition Ultra-High-Risk’ Individuals for Psychosis Using Spiking Neural Networks, *Schizophrenia,* 9, 10 (2023), https://doi.org/10.1038/s41537-023-00335-2





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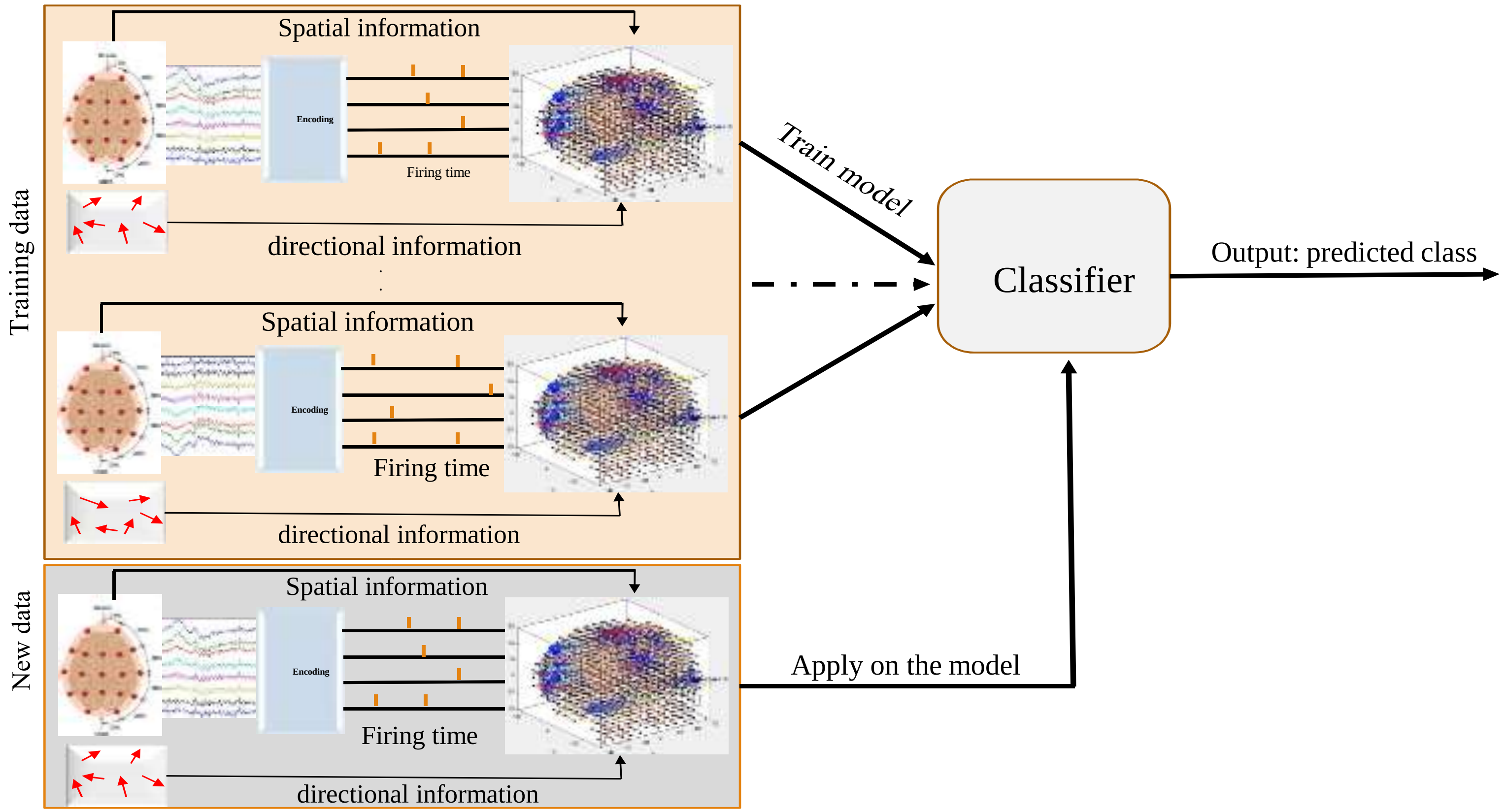
Integration of fMRI and DTI data in NeuCube

Case on response of schizophrenic patients to clozapine

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



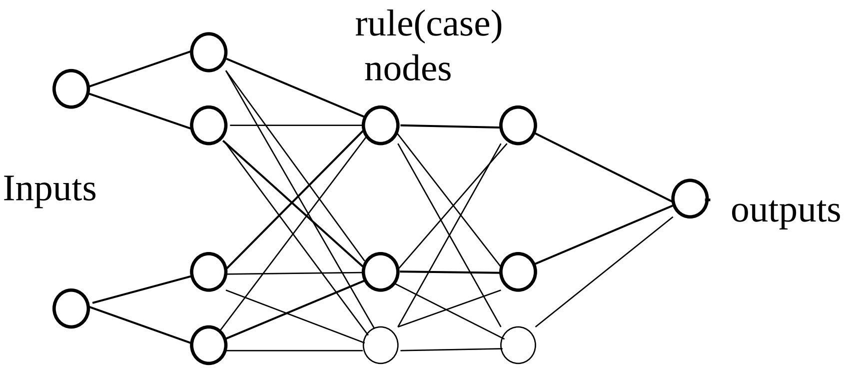
5. Explainability in STL

The role of fuzzy logic

Fuzzy neural networks: T.Yamakawa, B.Kosko, I. Rudash, T.Furuhashi, …

Evolving Fuzzy Neural Networks

– E.g.: EFuNN, DENFIS

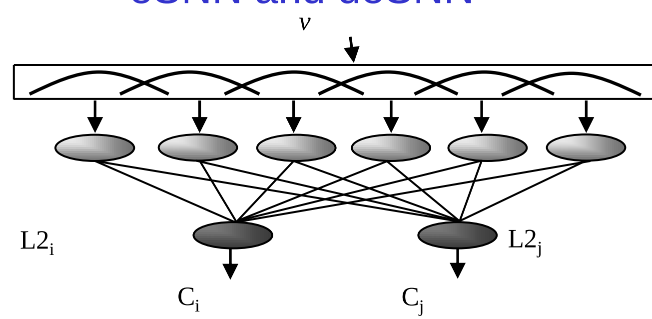


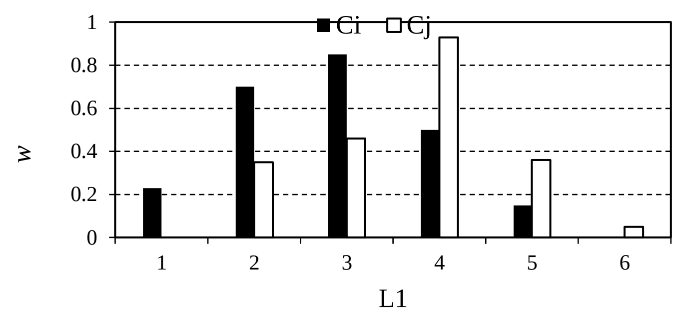
IF Input 1 is High and Input 2 is Low
THEN Output is Very High

Kasabov, N., and Song, Q., DENFIS: Dynamic Evolving Neural-Fuzzy Inference System and its Application for Time Series Prediction, IEEE Transactions on Fuzzy Systems, Vol. 10, 2, April, (2002) 144-154

Lotfi Zadeh (1920-2018)

eSNN and deSNN





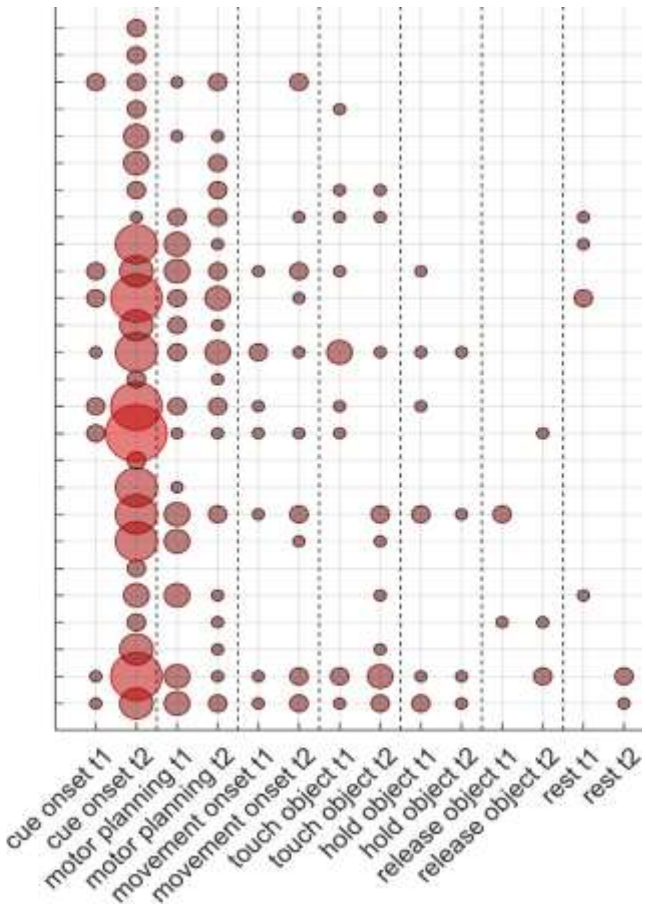
Rule 0: IF (v is SMALL) THEN C_i

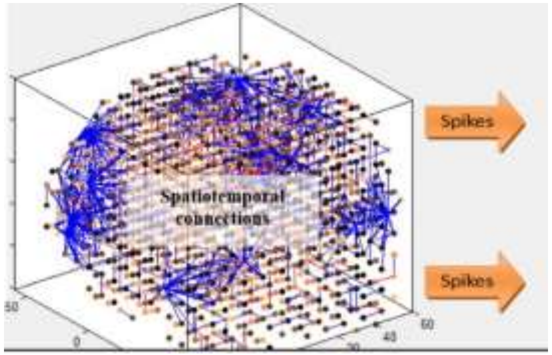
Rule 1: IF (v is LARGE) THEN C_j

S. Soltic and N. Kasabov (2010), Knowledge extraction from evolving spiking neural networks with rank order population coding. Int. J. Neural Syst., Vol. 20, No. 6, 2010, 437–445.

A biologically relevant fuzzy spatio-temporal rule (fSTR) can be extracted from a trained NeuCube on EEG data representing one movement of a subject (GAL)

IF (event E1 at about location S1 and about time T1) AND (event E2 ……..) … THEN (Action)





IF($E_{\text{cue-onset}}$: $F_{\text{cue-onset}}$, S{cue-onset}, $t_{\text{cue-onset}}$, P>0.8)
AND($E_{\text{motor-planning}}$: $F_{\text{motor-planning}}$, $S_{\text{motor-planning}}$, $t_{\text{motor-planning}}$, P>0.8)
AND($E_{\text{movement-onset}}$: $F_{\text{movement-onset}}$, $S_{\text{movement-onset}}$, $t_{\text{movement-onset}}$, P>0.8)
AND($E_{\text{touch-object}}$: $F_{\text{touch-object}}$, $S_{\text{touch-object}}$, $t_{\text{touch-object}}$, P>0.8)
AND($E_{\text{hold-object}}$: $F_{\text{hold-object}}$, $S_{\text{hold-object}}$, $t_{\text{hold-object}}$, P>0.9)
AND($E_{\text{release-object}}$: $F_{\text{release-object}}$, $S_{\text{release-object}}$, $t_{\text{release-object}}$, P>0.8)
AND(E_{rest} : F_{rest}, S_{rest}, t_{rest}, P>0.8)
THEN(Q = $Q_{\text{grasp-and-lift}}$).

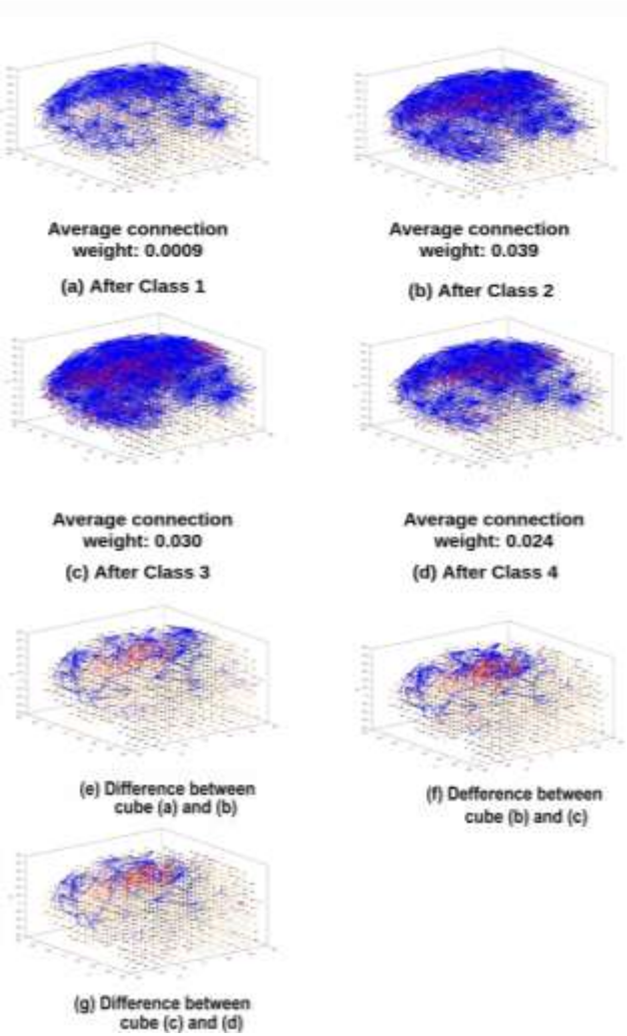
where Si = {Posterior Lobe, Temporal Lobe, Limbic Lobe, Frontal Lobe, Anterior Lobe, Occipital Lobe, Midbrain, Parietal Lobe}

K.Kumarasinghe, N.Kasabov, D.Taylor, Deep Learning and Deep Knowledge Representation in Spiking Neural Networks for Brain-Computer Interfaces, Neural Networks, vol.121 (2020),169-185, doi: https://doi.org/10.1016/j.neunet.2019.08.029.

Kasabov, N., Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence, Springer (2019), 750p., https://www.springer.com/gp/book/9783662577134

Transfer learning of fuzzy spatio-temporal rules in NeuCube

N.K. Kasabov, Tan, Yongyao Tan; Doborjeh, Maryam; Tu, Enmei; Yang, Jie (2023): Transfer Learning of Fuzzy Spatio-Temporal Rules in the NeuCube Brain-Inspired Spiking Neural Network: A Case Study on EEG Spatio-temporal Data. TechRxiv. Preprint. https://techrxiv.org), https://doi.org/10.36227/techrxiv.21781103.v1, accepted IEEE TrFS (June 2023)



Average connection weight: 0.0009
(a) After Class 1

Average connection weight: 0.039
(b) After Class 2

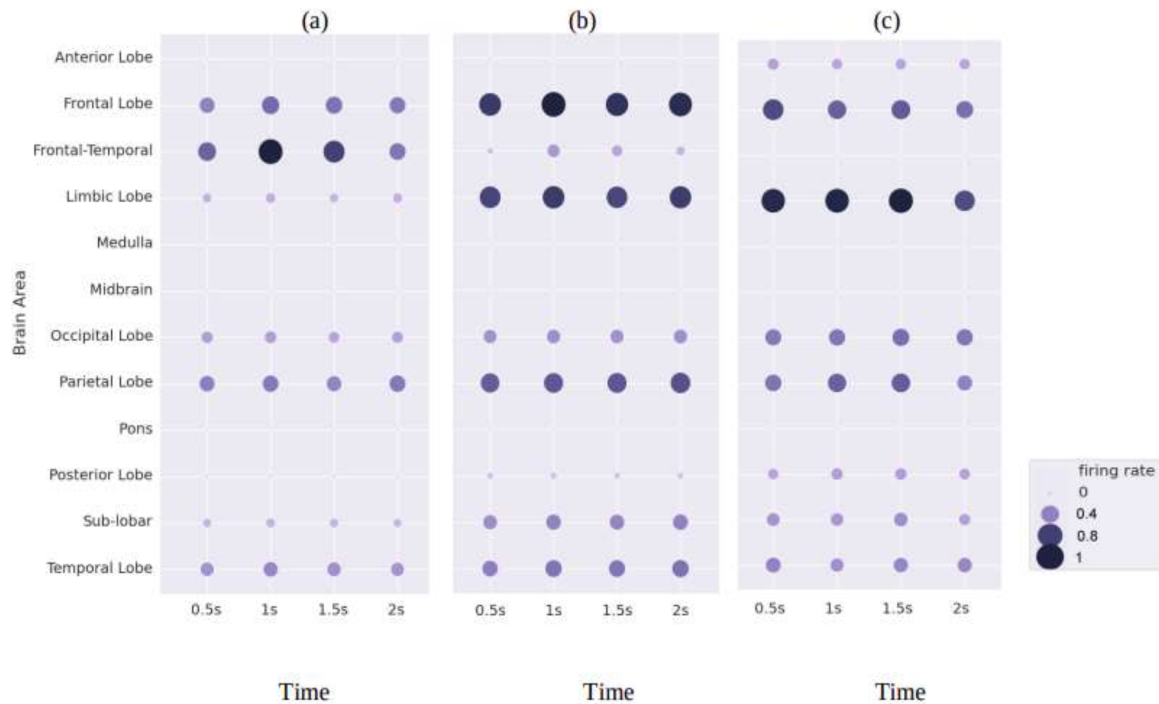
Average connection weight: 0.030
(c) After Class 3

Average connection weight: 0.024
(d) After Class 4

(e) Difference between cube (a) and (b)

(f) Defference between cube (b) and (c)

(g) Difference between cube (c) and (d)



FSTR for (a):

IF (firing rate of $area_{1,1}(t1)$ is SMALL and $area_{2,1}$ $(t1)$ is MEDIUM (at time t1 about 0.5s) AND

AND (firing rate of $area_{1,2}(t2)$ is SMALL and $area_{2,2}(t2)$ is MEDIUM and $area_{3,2}(t2)$ is HIGH (at time t2 bout 1s)

AND (firing rate of $area_{1,3}(t3)$ is SMALL and $area_{2,3}(t3)$ is MEDIUM (at time t3 about 1.5s)

AND (firing rate of $area_{1,4}(t4)$ is SMALL and $area_{2,4}(t4)$ is MEDIUM (at time t4 about 2s)

THEN (This is the transfer of knowledge (the difference) in the SNNcube activity after it was trained on task 2 after task 1)

Note: Task 1: Reach for a glass of water, drink, and place the glass on the table. ;

Task 2: Throw a ball from the right hand to the left hand.

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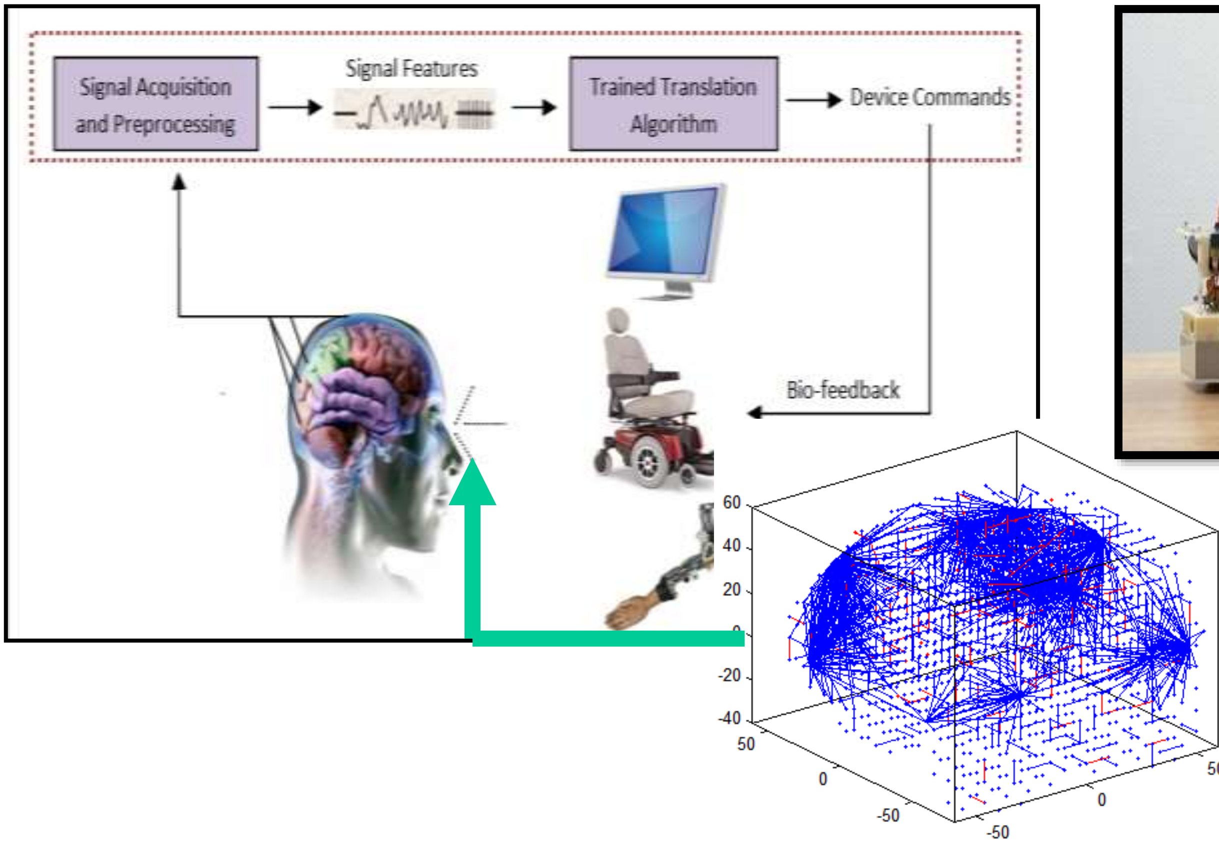
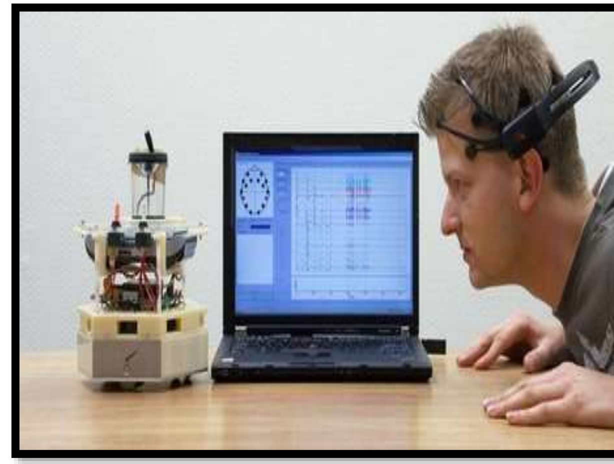
6. Human-machine symbiosis based on STL

Brain-Computer Interfaces (BCIs) are systems trained on human brain data (e.g. EEG) for humans to communicate directly with computers or external devices through their brains

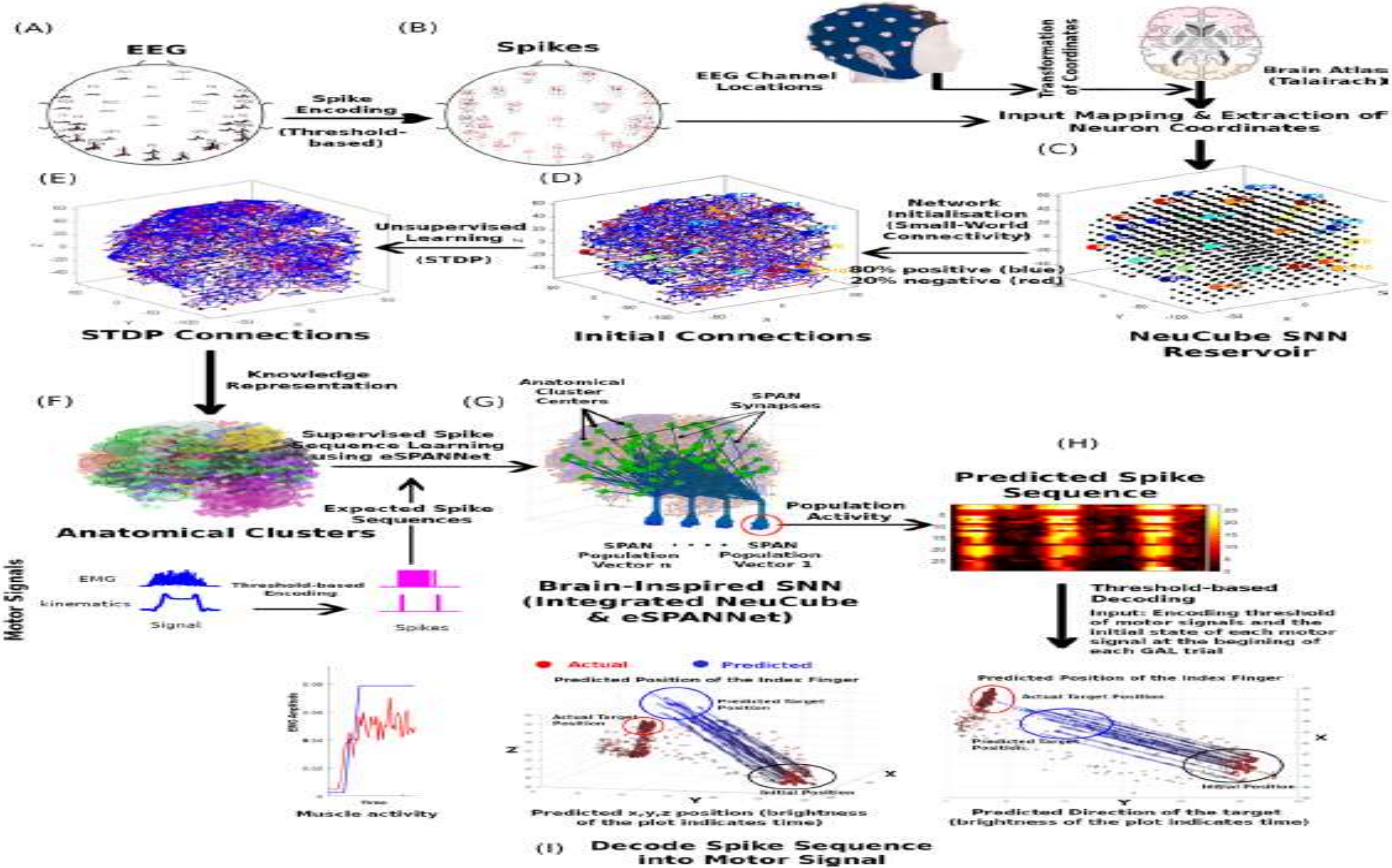
BI-BCI are designed using a brain template.





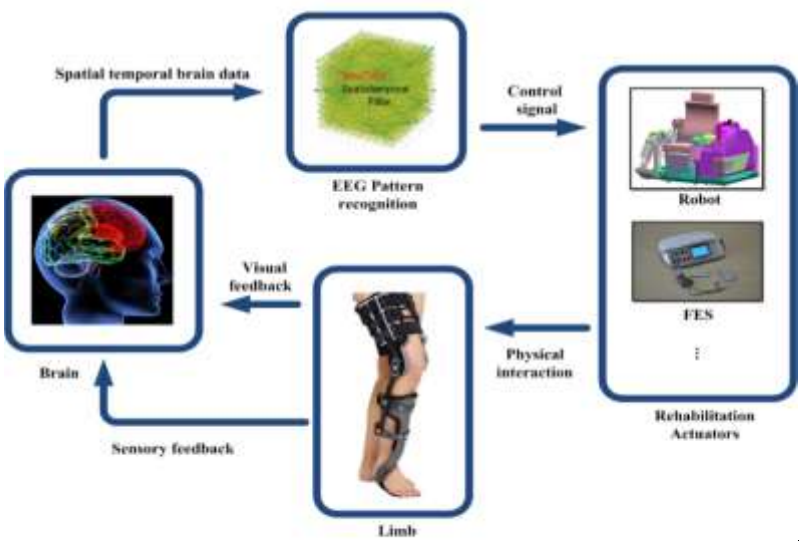
STL for brain-body control

Kumarasinghe, K., Kasabov, N. & Taylor, D. Brain-inspired spiking neural networks for decoding and understanding muscle activity and kinematics from electroencephalography signals during hand movements. *Sci Rep* **11,** 2486 (2021). https://doi.org/10.1038/s41598-021-81805-4 (ranked 11 in SR in Neuroscience for 2021)

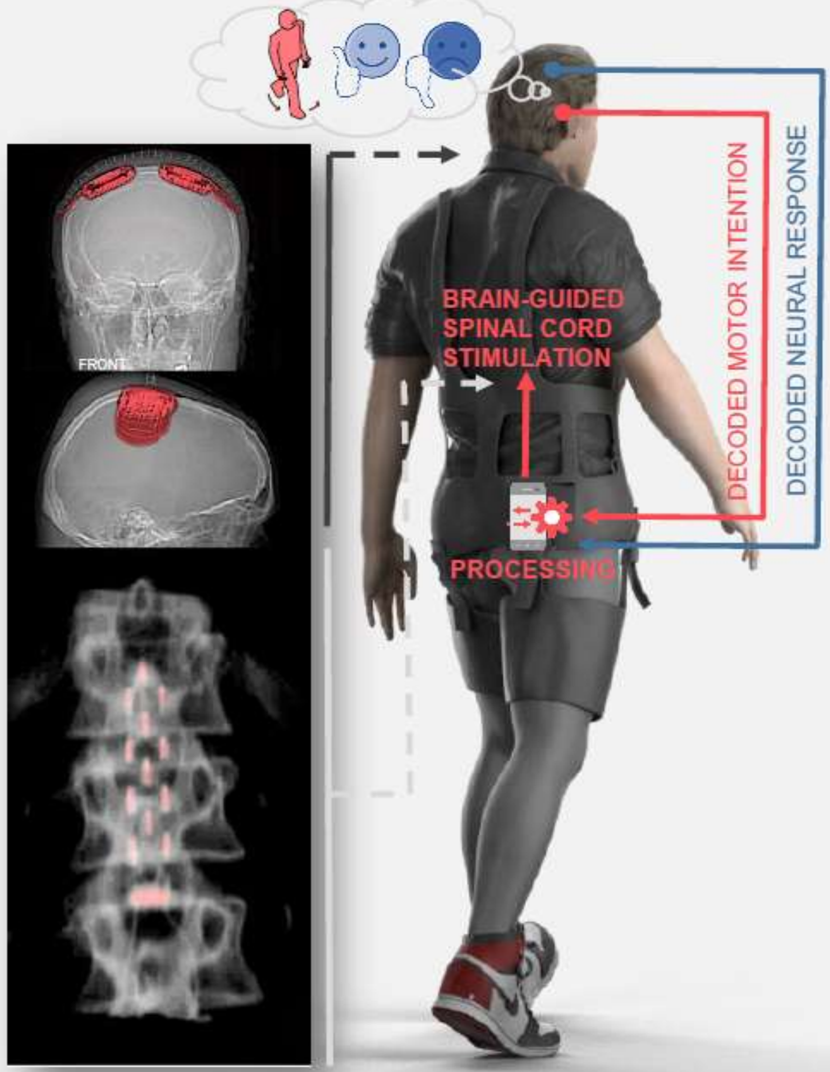


BI-SNN for BI-BCI in robot control and neurorehabilitation

(with Prof. Zeng-Guang Hou, CASIA, Beijing China)



Fully embedded auto-adaptive Brain Machine Interface



Implantable measure – stimulation technology

- Chronic wireless brain recording WIMAGINE implant
- Spinal cord stimulation ONWARD implant
- 2 Clinical trials ongoing: brain machine interface proof of concept

Auto-adaptive motor BMI decoding

- Natural control based on patient's intention
- Multiple degrees of freedom control
- Decoding of Neural response linked to intention/action coherence
- Real-time auto-adaptive decoder
- Assistance free
- Neuromorphic decoding algorithms

IICT- BAS

Brain-guided spinal cord Stimulation

- Epidural Electrical Targeted dynamic stimulation
- Auto-adaptative stimulation Patterns

Miniaturization of BMI technology

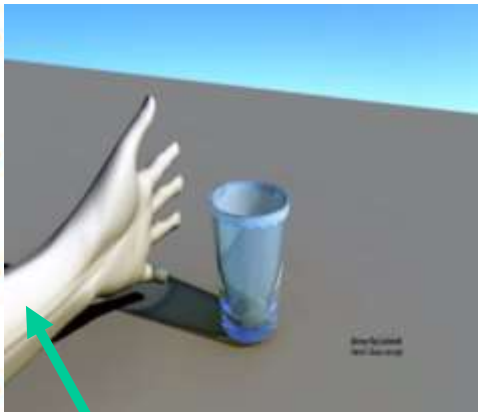
- Low power integrated circuit for accelerating the decoding algorithms
- High system level integration
- Portable battery-powered solution

NEMO-BMI, HORIZON-EIC-2021-PATHFINDERCHALLENGES-01-02, France, Neth., Swiss, Bulgari

STL for modelling human- VR/AR interaction

Detecting and predicting cybersickness

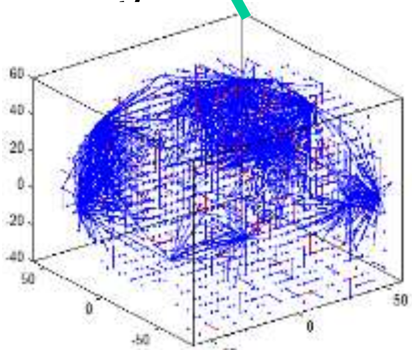
Yang AHX, Kasabov NK, Cakmak YO. Prediction and Detection of Virtual Reality induced Cybersickness: A Spiking Neural Network Approach Using Spatiotemporal EEG Brain Data and Heart Rate Variability. https://doi.org/10.21203/rs.3.rs-2383481, Brain Informatics, Springer-Nature, May, 2023.

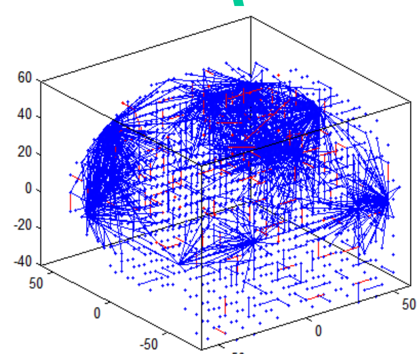


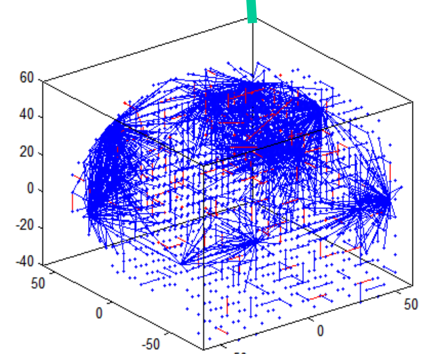
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.

A virtual environment to control a quadrotor using EEG signals.

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



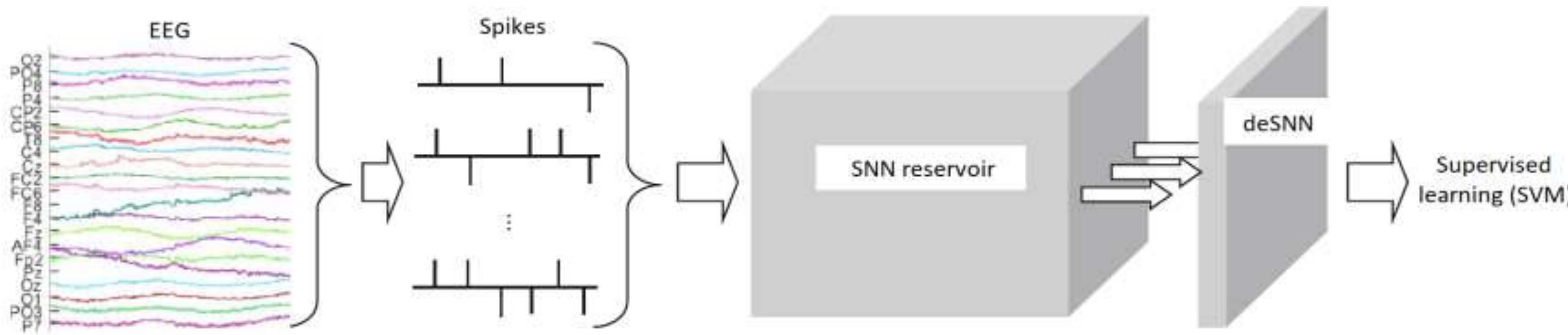


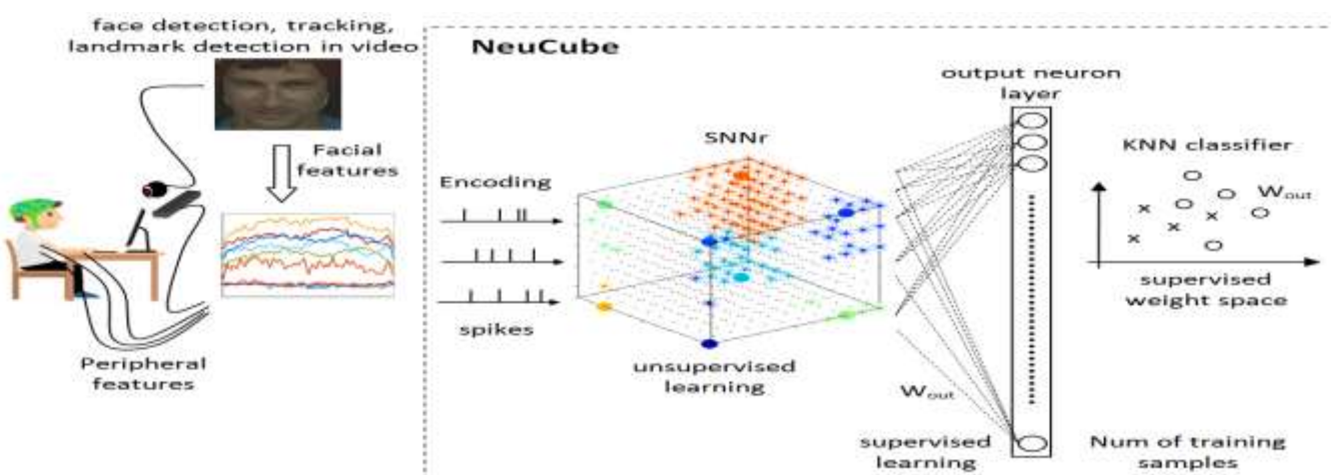


STL for affective computing with multimodal data

Wael Alzhrani, **Maryam Doborjeh**, Zohreh Doborjeh and Nikola Kasabov, Emotion Recognition and Understanding Using EEG Data in a Brain-Inspired Spiking Neural Network Architecture. *Proc. IJCNN 2021*.

C.Tan, M.Sarlija, N.Kasabov, NeuroSense: Short-Term Emotion Recognition and Understanding Based on Spiking Neural Network Modelling of Spatio-Temporal EEG Patterns, Neurocomputing, 2021.





C. Tan; G. Ceballos; N. Kasabov; N. Samaniyam, FusionSense: Emotion Classification using Feature Fusion of Multimodal Data and Deep learning in a Brain-inspired Spiking Neural Network, Sensors, MDPI, Sept. 2020

STL across subjects: hyper-scanning

B.Kelsen, A.Sumich, N.Kasabov, S.Liang, G.Wang, What has social neuroscience learned from hyperscanning studies of spoken communication? A systematic review. Neuroscience&Biobehavioural Reviews, 3 September 2020, https://doi.org/10.1016/j.neubiorev.2020.09.008; https://www.sciencedirect.com/science/article/abs/pii/S0149763420305650

LAstolfi, J Toppi, FDe Vico Fallani, G Vecchiato, F Cincotti, C. Wilke, HYuan, D Mattia, S Salinari, B He, and F Babiloni, I, **Imaging the Social Brain by Simultaneous Hyperscanning During Subject Interaction,** EEE Intell Syst. 2011 Oct; 26 (5): 38–45.

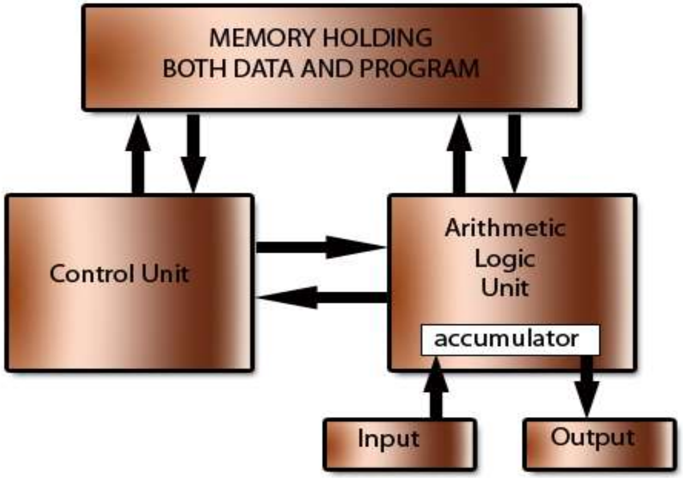
7. STL for AI Sustainability

From von Neumann principles and Atanassov's ABC to Neuromorphic Computers

- The computer architecture of John von Neumann separates data and programmes (kept in the memory unit) from the computation (ALU); uses *bits*. First machine ABC by Atanassov and Berry.
- A Neuromorphic architecture integrates the data, the programme and the computation in a SNN structure, similar to how the brain works; uses *spikes* (bits at times) (e.g. S.Furber SpiNNaker; IBM True North; Akira; ETH/EZH Indiveri)
- Intel Loihi:

- A quantum computer uses *q-bits* (bits in a superposition) (IBM D-Wave).

The Von Neumann or Stored Program architecture



(c) www.teach-ict.com

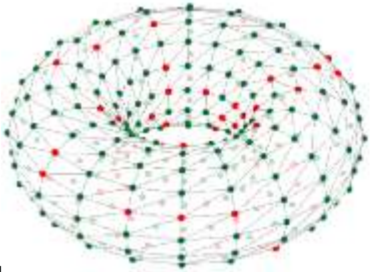
N. Sengupta et al, (2018), From von Neumann architecture and Atanasoffs ABC to Neuromorphic Computation and Kasabov's NeuCube: Principles and Implementations, Chapter 1 in: Advances in Computational intelligence, Jotzov et al (eds) Springer 2018.

Neuromorphic hardware

High speed and low power consumption. Energy and pollution sustainable!

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

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



INI Zurich SNN chips (Giacomo Indiveri)

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

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

FPGA SNN realisations (McGinnity, Ulster and NTU)

Intel Loihi

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NeuCube SNN development environment for STL

(a) Matlab version: www.kedri.aut.ac.nz/neucube; and https://github.com/KEDRI-AUT/NeuCube-Matlab

(b) Python version (Balkaran Singh) https://github.com/KEDRI-AUT/NeuCube-Py

(c) Version to work on SpiNNaker (Behrenbeck): https://github.com/behrenbeck/NeuCube_SpiNNaker.

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

8. Opportunities for STL systems across application domain areas

Brain data modelling

Deep learning and deep knowledge representation of EEG data
Brain Disease Diagnosis and prognosis based on EEG data
Deep learning and deep knowledge representation of fMRI data
Integrating time-,space and orientation .

Audio-visual data and brain computer interfaces

Audio and visual information processing in the brain and its modelling
Deep learning and modelling of audio and visual and multimodal audio-visual data in BI-SNN
Brain-computer interfaces (BCI) using BI-SNN

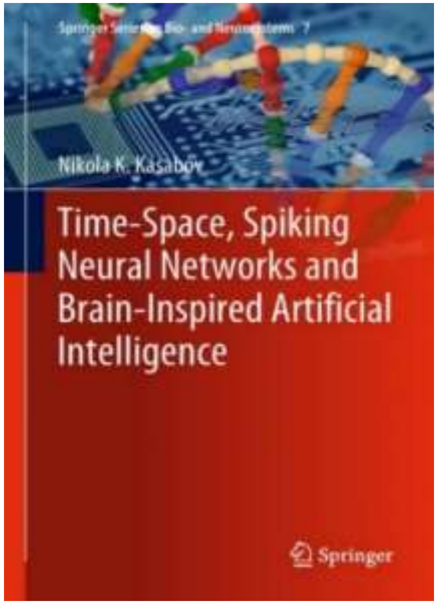
SNN in Bio- and Neuroinformatics

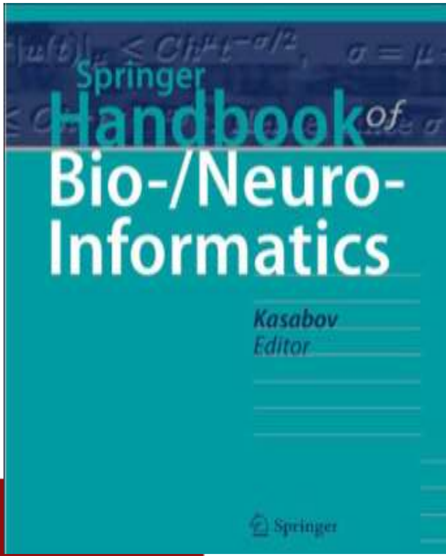
Computational modelling and pattern recognition in Bioinformatics
Computational neurogenetic modelling
Computational framework for personalised modelling. Applications in Bioinformatics.
Personalised modelling for integrated static and dynamic data.
Applications in neuroinformatics

Application for multisensory streaming data

Cybersecurity
Environmental predictive modelling
Predicting earthquakes and nature disasters
Financial and economic data

Software for neuromorphic computer systems





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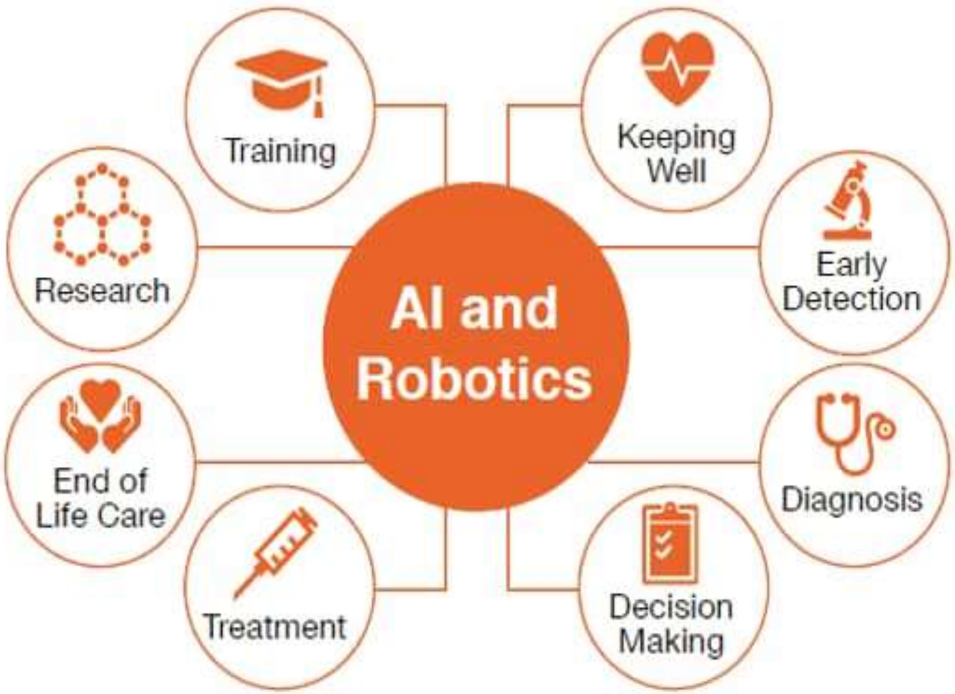
STL in Medicine and Health

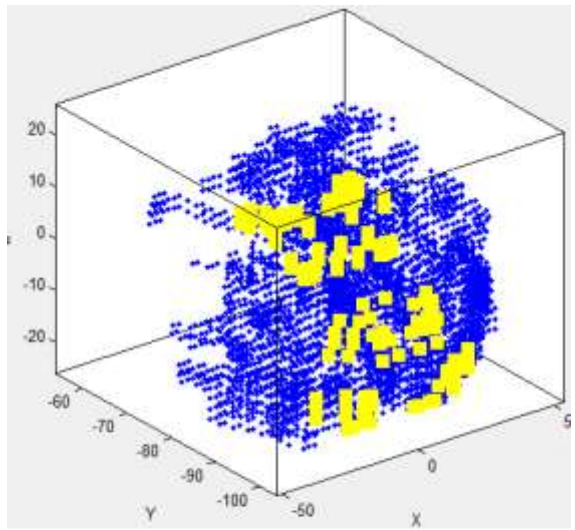
AI in Medicine and Health
Molecular research: DNA and gene data analysis; vaccine designs; microbiology; …
Precision medicine : Machine learning for personalised predictive modelling
Global health data analysis: pandemics; population health.
Image analysis: brain images; EEG, fMRI, DTI,…
Robotics: - surgical robots; - patient care robots - Nano robots (drug delivery in the body) - Brain implants
Brain-machine interfaces (BMI) for neurorehabilitation
Many other



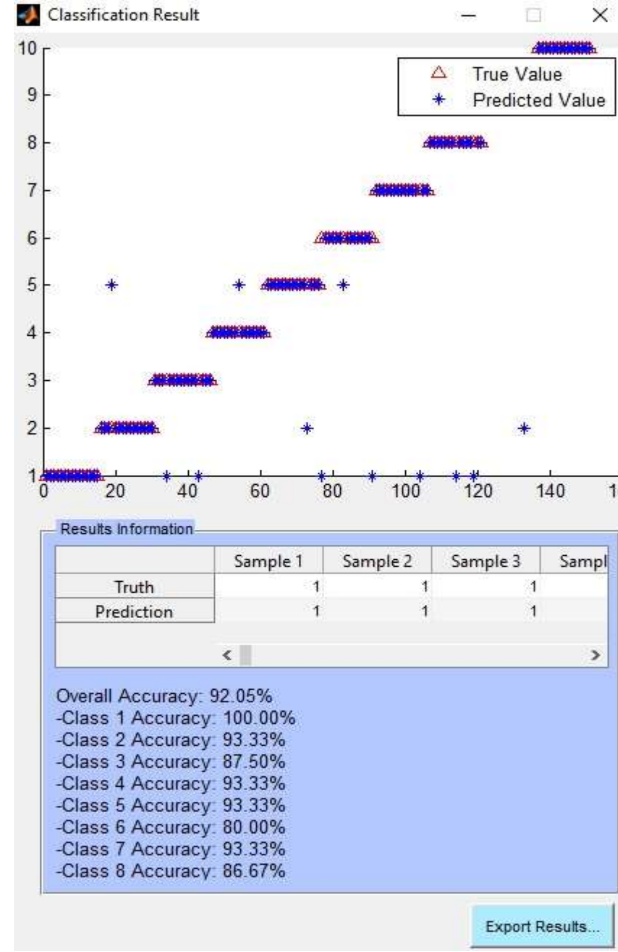
https://www.pwc.com/gx/en/industries/healthcare/publications/ai-robotics-new-health/transforming-healthcare.html

STL of moving objects using DVS and retinotopic mapping in NeuCube

30000 moving digits in 8 fonts and sizes from DVS MNIST



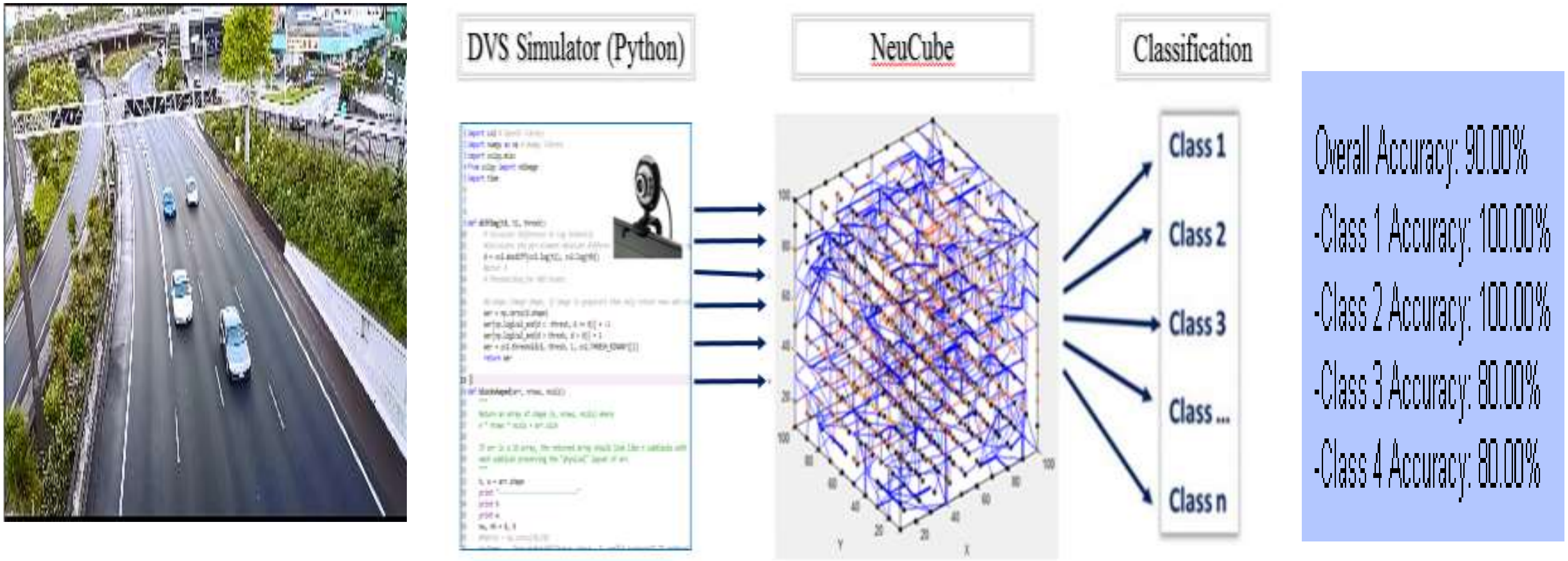
NeuCube with 4262 neurons from V1 and V2



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

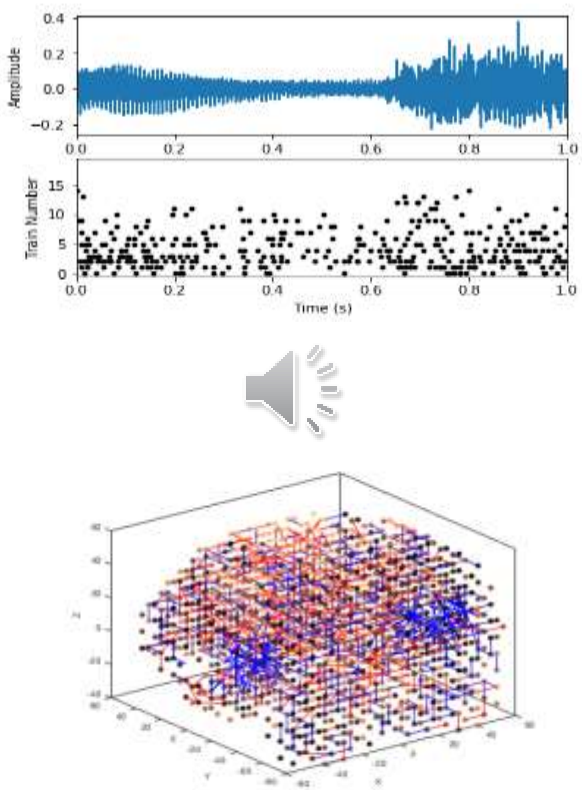
NeuCube and DVS on mobile platforms - fast eSTL for moving object recognition

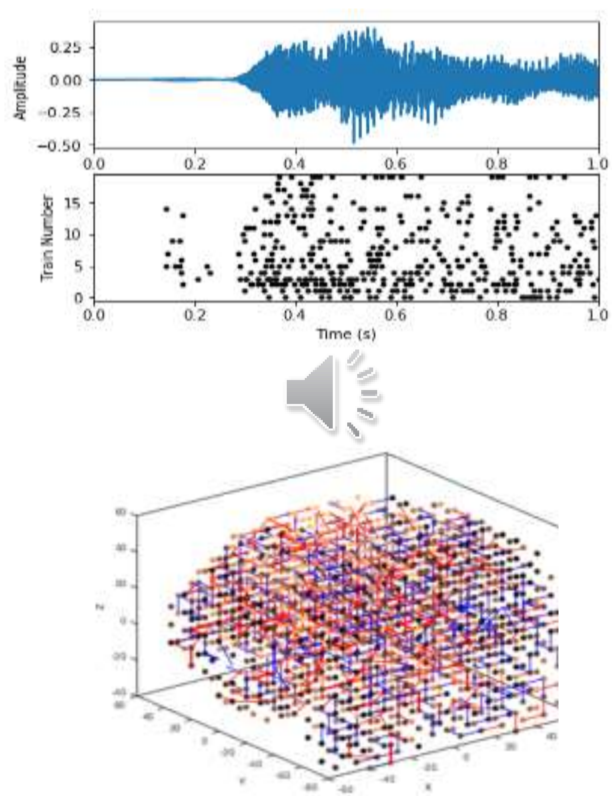
- Autonomous vehicles
- Surveillance systems
- Cybersecurity
- Military applications

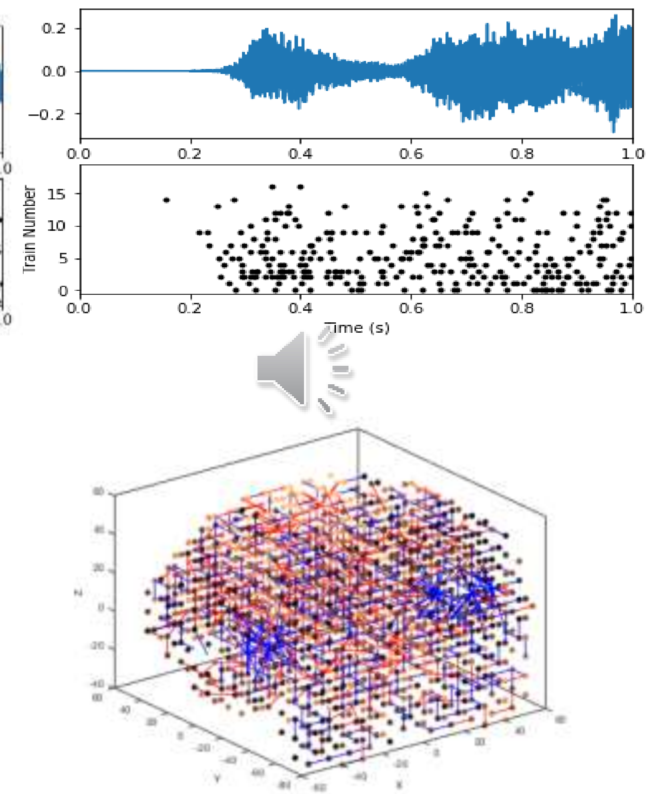


STL of audio-, visual and audio-visual data in BI-SNN

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



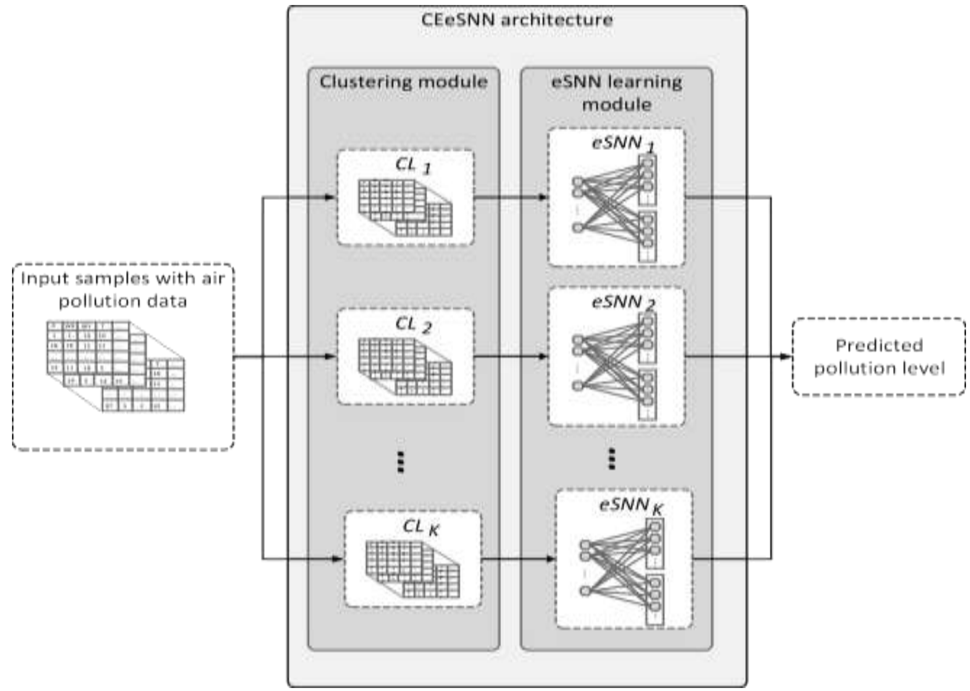




	Mozart	Bach	Vivaldi
Predicted 1	171	3	1
Predicted 2	9	176	1
Predicted 3	0	1	178

Predictive STL of streaming data from pollution sensors

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



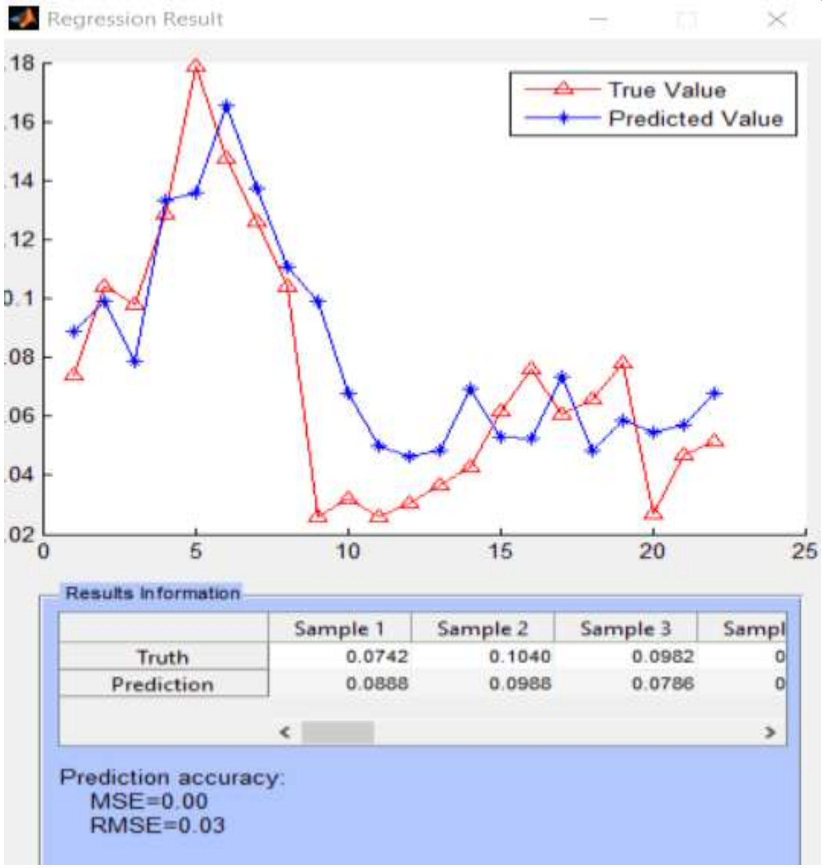
P. S. P Maciaga, N. K. Kasabov, M. Kryszkiewicza, R. Benbenik, Prediction of Hourly Air Pollution in London Area Using Evolving Spiking Neural Networks, Environmental Modelling and Software, Elsevier, vol.118, 262-280, 2019, https://www.sciencedirect.com/science/article/pii/S1364815218307448?dgcid=author

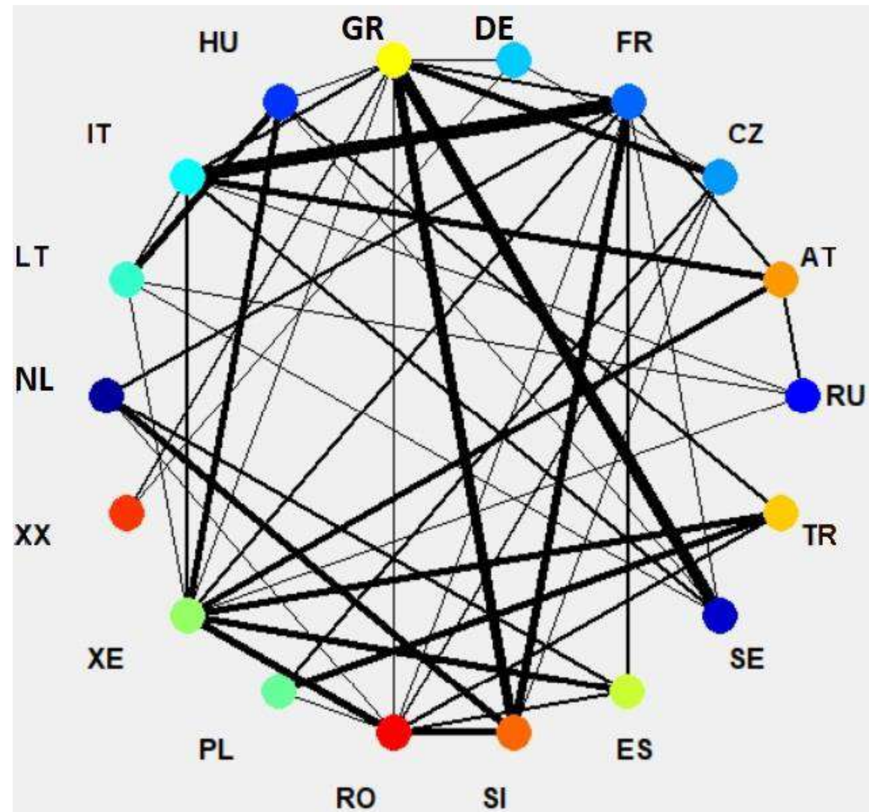
Hengyuan Liu, Guibin Lu,Yangjun Wang, Nikola Kasabov, Evolving spiking neural network model for PM2.5 hourly concentration prediction based on seasonal differences: A case study on data from Beijing and Shanghai, Aerosol and Air Quality Research, vol.21, Issue 2, Feb. 2021, 200247, https://doi.org/10.4209/aaqr.2020.05.0247

STL of financial time series data

I. Abouhassan, N. Kasabov, G. Popov and R. Trifonov, "Why Use Evolving Neuro-Fuzzy and Spiking Neural Networks for incremental and explainable learning of time series? A case study on predictive modelling of trade imports and outlier detection," *2022 IEEE 11th International Conference on Intelligent Systems (IS)*, Warsaw, Poland, 2022, pp. 1-7, doi: 10.1109/IS57118.2022.10019673.

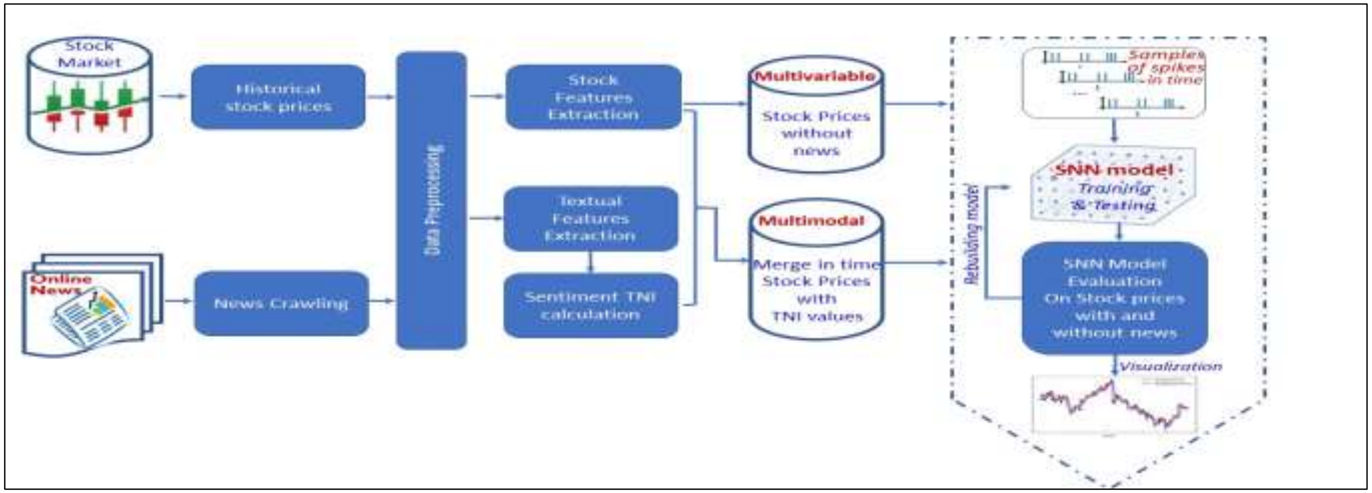
Example: **USING NEUCUBE on a CASE STUDY ON BULGARIAN PETROLEUM OIL IMPORTS**

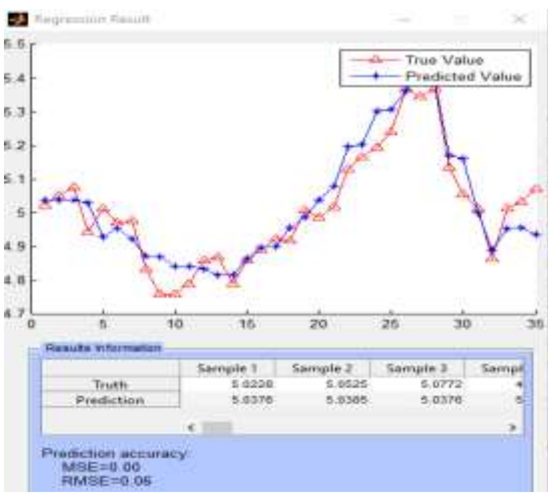


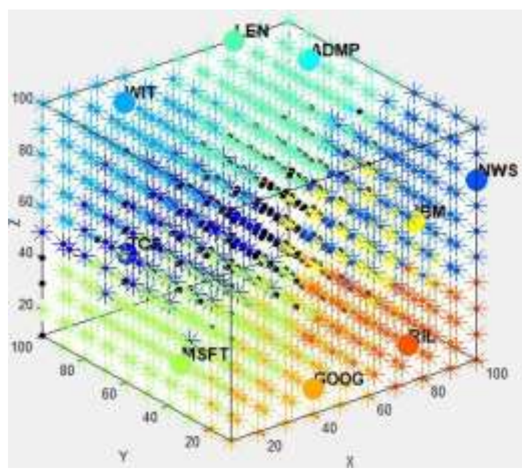


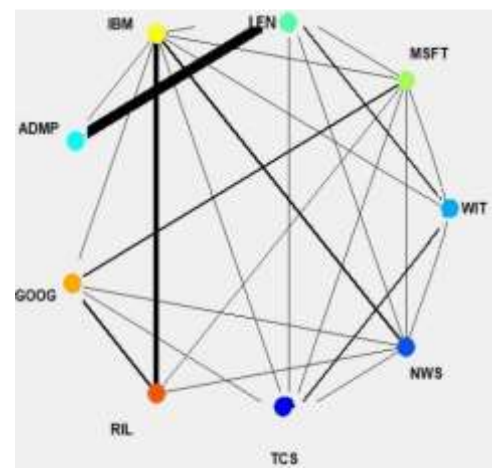
STL of multimodal streaming data: Financial data + on-line news

Nikola K. Kasabov, Iman AbouHassan, Vinayak G.M. Jagtap, Parag Kulkarni, Spiking neural networks for predictive and explainable modelling of multimodal streaming data on the Case Study of Financial Time Series Data and on-line news, SREP, Nature, pre-print on the Research Square, DOI: https://doi.org/10.21203/rs.3.rs-2262084/v1









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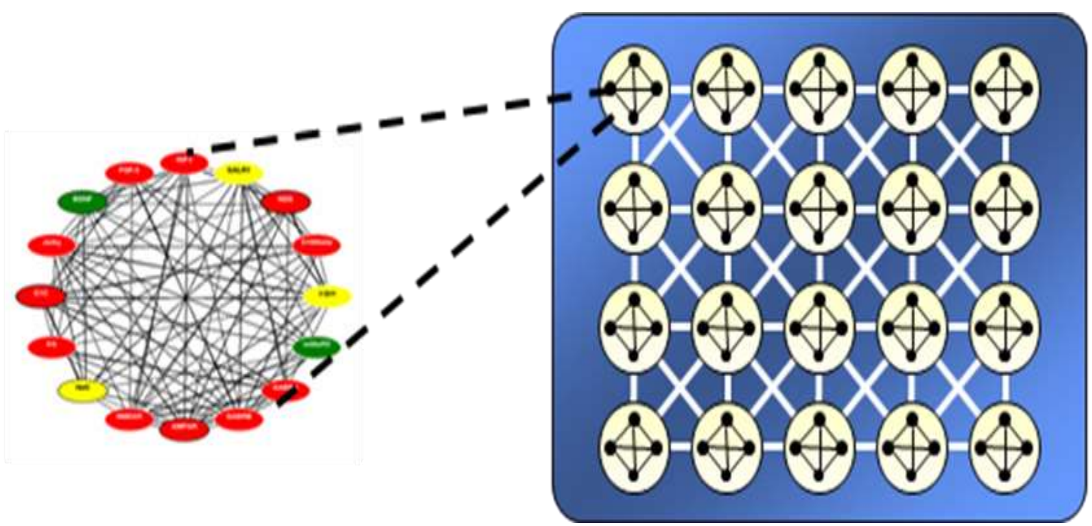
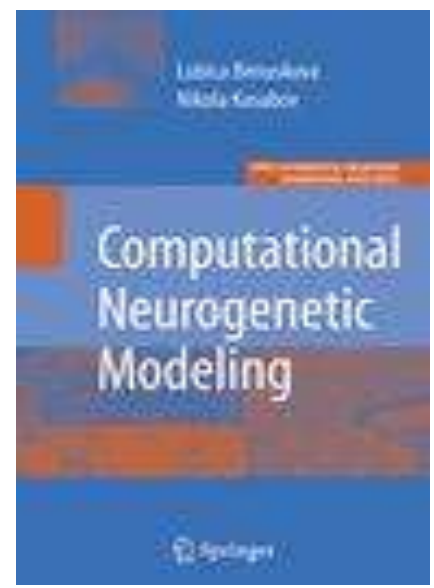
Computational Neuro-Genetic Modelling (CNGM)

- Benuskova and Kasabov (2007)

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

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





Quantum-enhanced neurocomputation: Is this the ultimate STL paradigm?

Quantum information principles: the model of the atom; superposition; entanglement, interference, parallelism (M.Planck, A.Einstein, Niels Bohr, W.Heisenberg, John von Neumann, **E. Rutherford**)

Ernest Rutherford (1871-1937)

- *Quantum bits (qu-bits)*

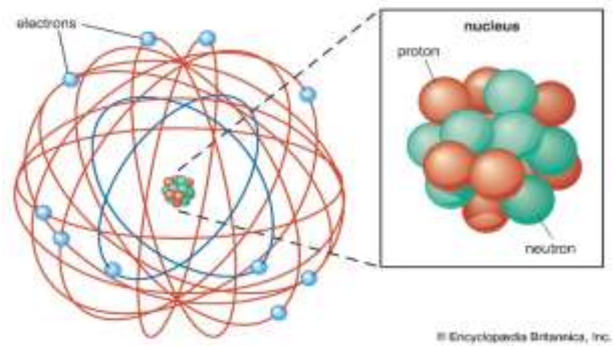
$$|\alpha|^2 + |\beta|^2 = 1 \qquad |\Psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

- *Quantum vectors (qu-vectors)*

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

- *Quantum gates*

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



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

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16. NeuCom: https://theneucom.com
17. KEDRI R&D Systems are available from: http://www.kedri.aut.ac.nz

New upcoming book:

Evolvable and explainable spatio-temporal learning in bio/neuro systems, mathematics and machines, N.Kasabov, Springer, 2024.