Advanced Artificial Intelligence Technologies and Applications

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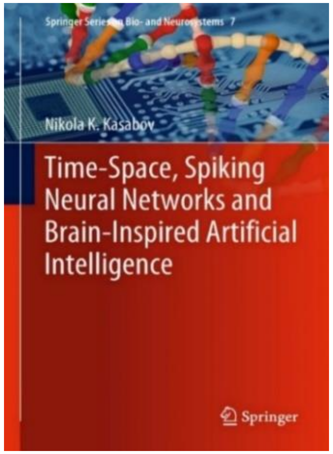
Advanced Artificial Intelligence Technologies and Applications

1. AI and the evolution of its principles. Evolving processes in Time and Space (Ch1, 3-19)
2. From Data and Information to Knowledge. Fuzzy logic. (Ch1,19-33 + extra reading)
3. Artificial neural networks - fundamentals. (Ch2, 39-48). Computational modelling with NN. Tut1: NeuCom.
4. Deep neural networks (Ch.2, 48-50 + extra reading).
5. Evolving connectionist systems (ECOS) (Ch2, 52-78). Tutorial 2: ECOS in NeuCom.
6. Deep learning and deep knowledge representation in the human brain (Ch3)
7. Spiking neural networks (Ch4). Evolving spiking neural networks (Ch5)
8. Brain-inspired SNN. NeuCube. (Ch.6). Tutorial 3: NeuCube software (IA)
9. From von Neuman Machines to Neuromorphic Platforms (Ch20 , 22)
10. Other neurocomputers: Transformers.
11. Evolutionary and quantum inspired computation (Ch.7)
12. AI applications for brain data: EEG, fMRI (Ch.8-11)
13. Brain-computer interfaces (BCI) (Ch.14)
14. AI applications for audio-visual information (Ch.12,13). AI for language modelling.
15. AI in bioinformatics and neuroinformatics (Ch15,16, 17,18)
16. AI applications for multisensory environmental data (Ch19).
17. AI in finance and economics (Ch19)



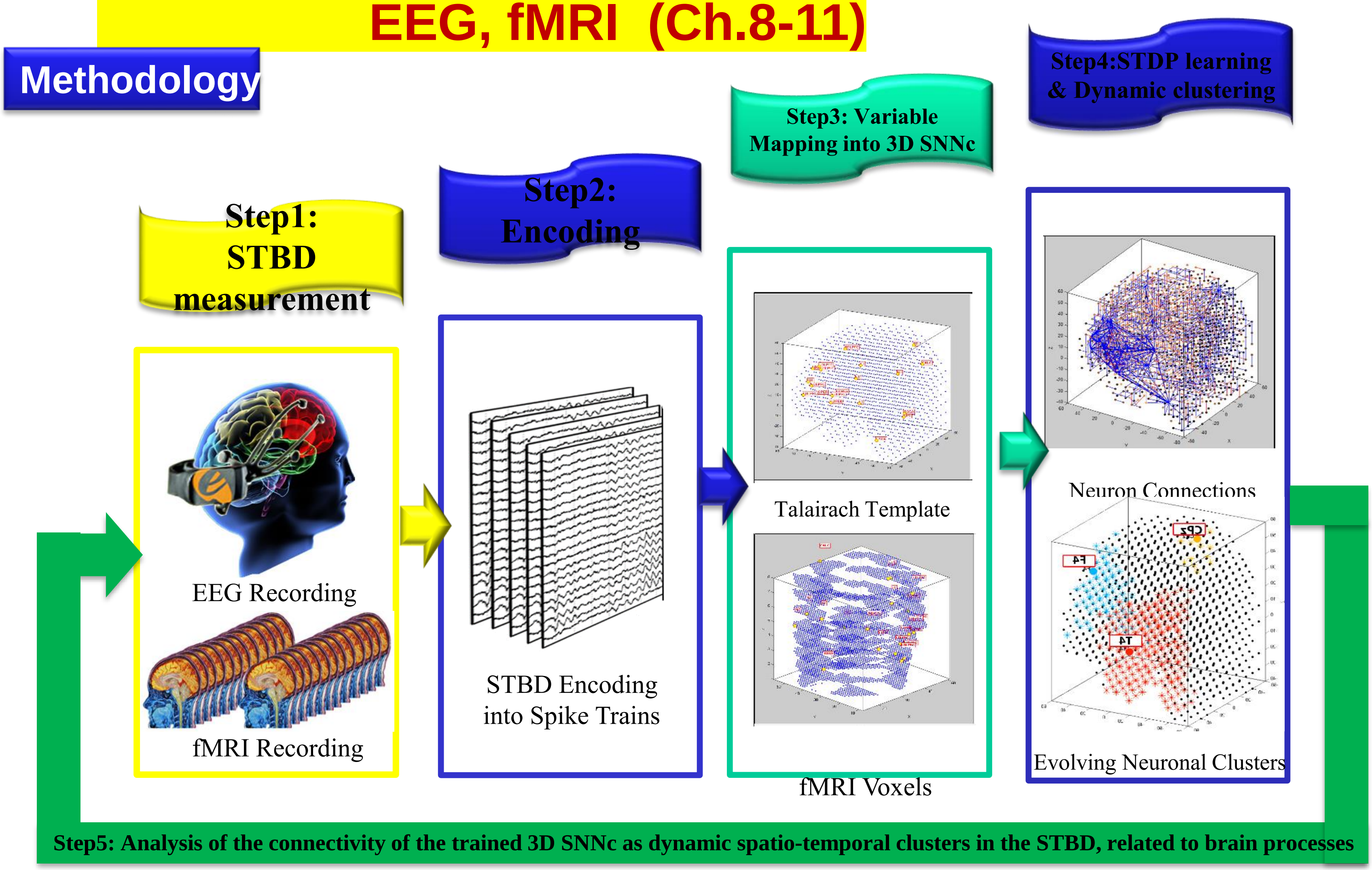
Course book: N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence Springer, 2019, https://www.springer.com/gp/book/9783662577134

Additional materials: https://www.knowledgeengineering.ai/china

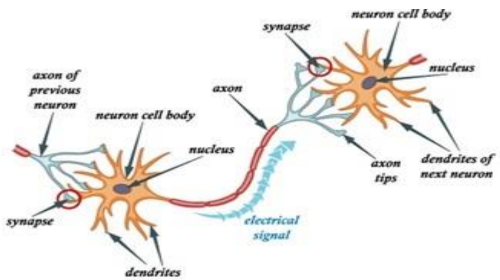
ZOOM link for all lectures: https://us05web.zoom.us/j/4658730662?pwd=eFN0eHRCN3o4K0FaZ0lqQmN1UUgydz09

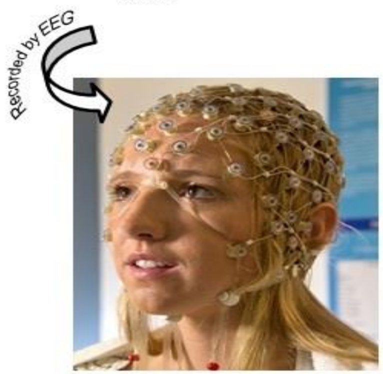
Lecture 12. AI applications for brain data

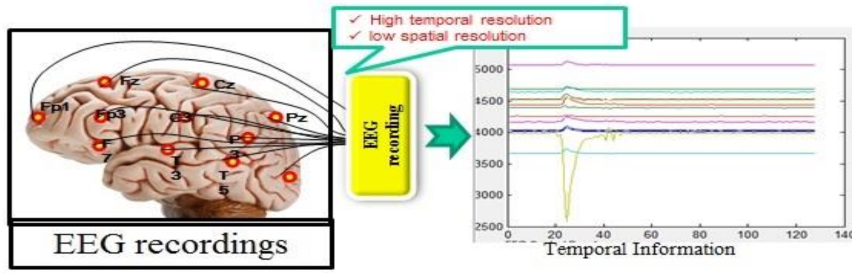
EEG, fMRI (Ch.8-11)

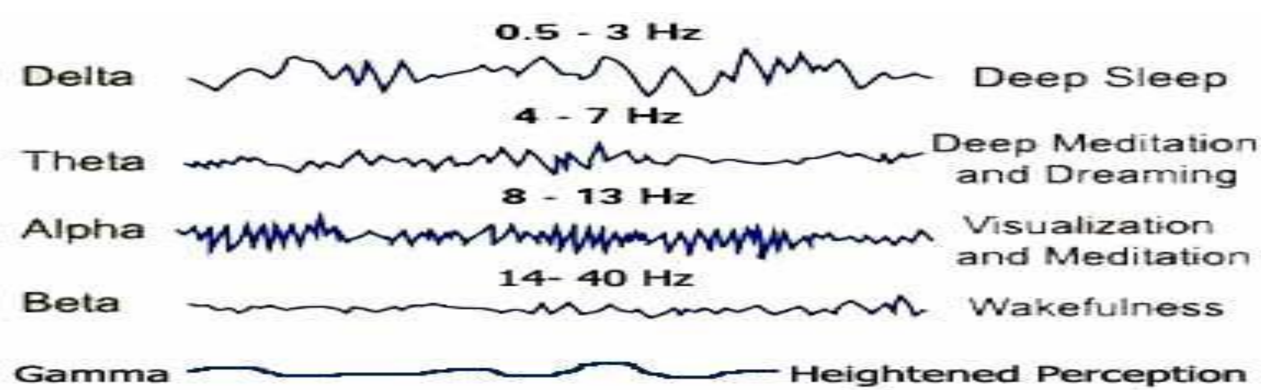


What are EEG brain signals?

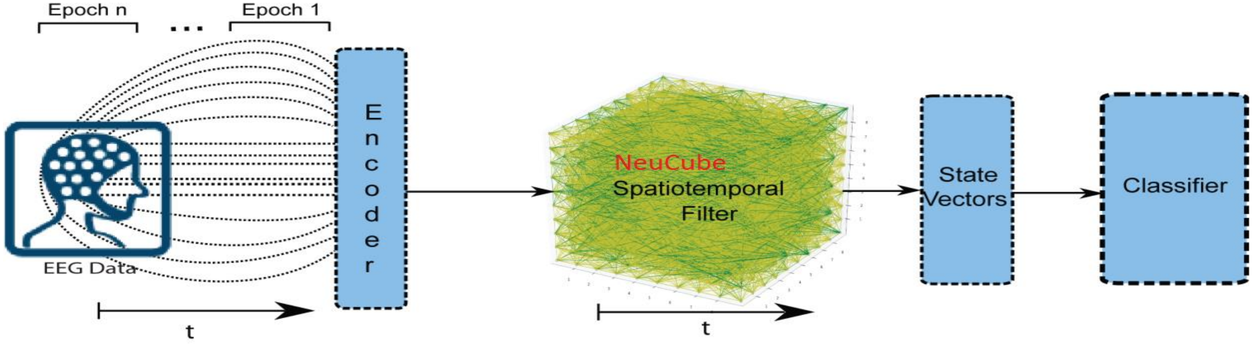


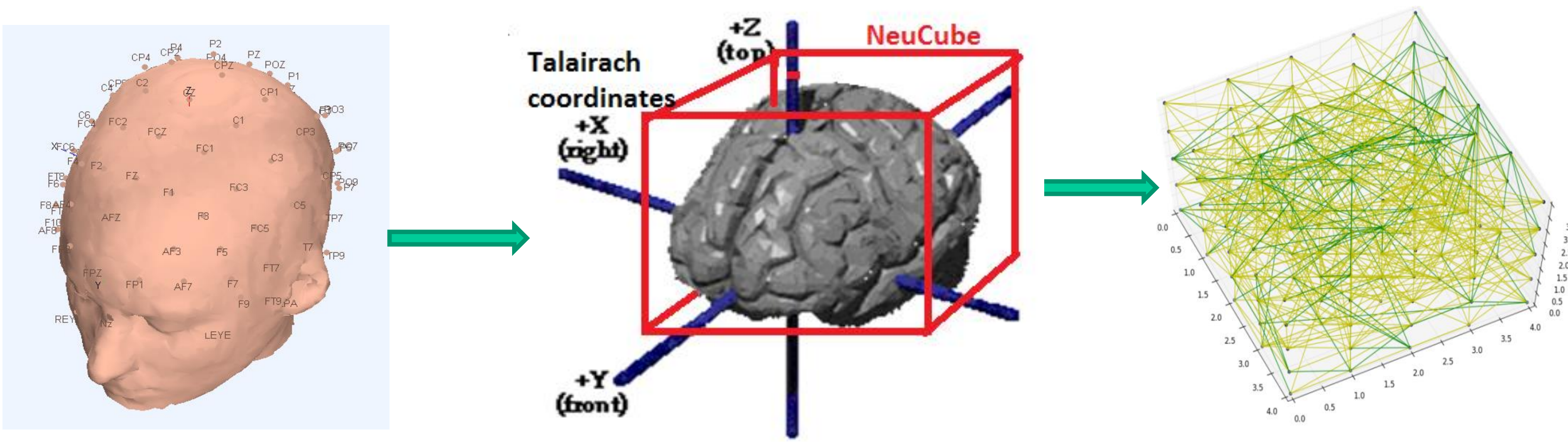






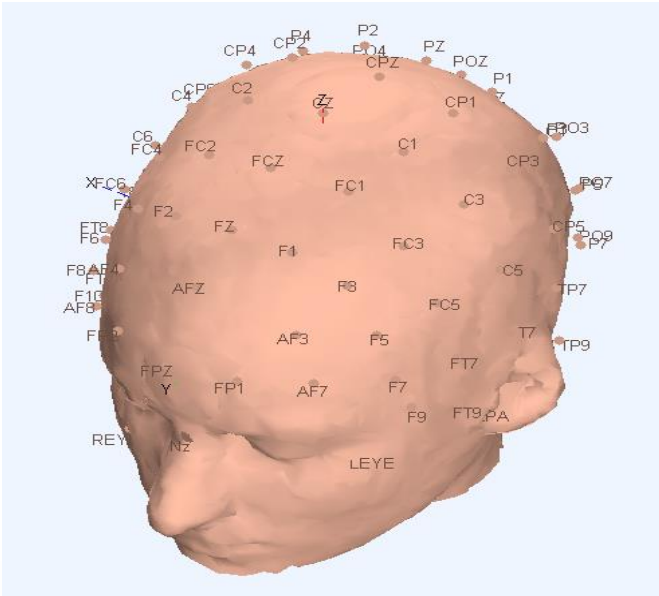
Mapping, learning and mining EEG data in NeuCube (Ch.8)

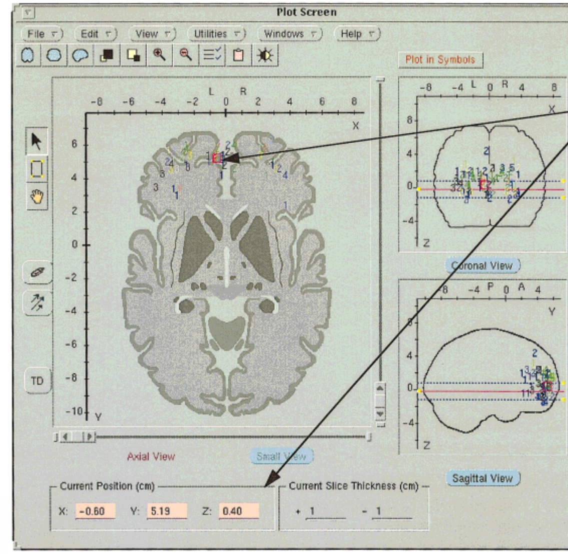




Same brain 3D coordinates (e.g. Talairach, MNI) are used for the allocated spiking neurons in the SNNc where the input data is mapped and the SNNc is analysed after training with the EEG data

Mapping EEG data into NeuCube





Talairach Label

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

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

Query on Brodmann Area 10 yielded:

- **32 papers**
- **46 experiments**

Table 1

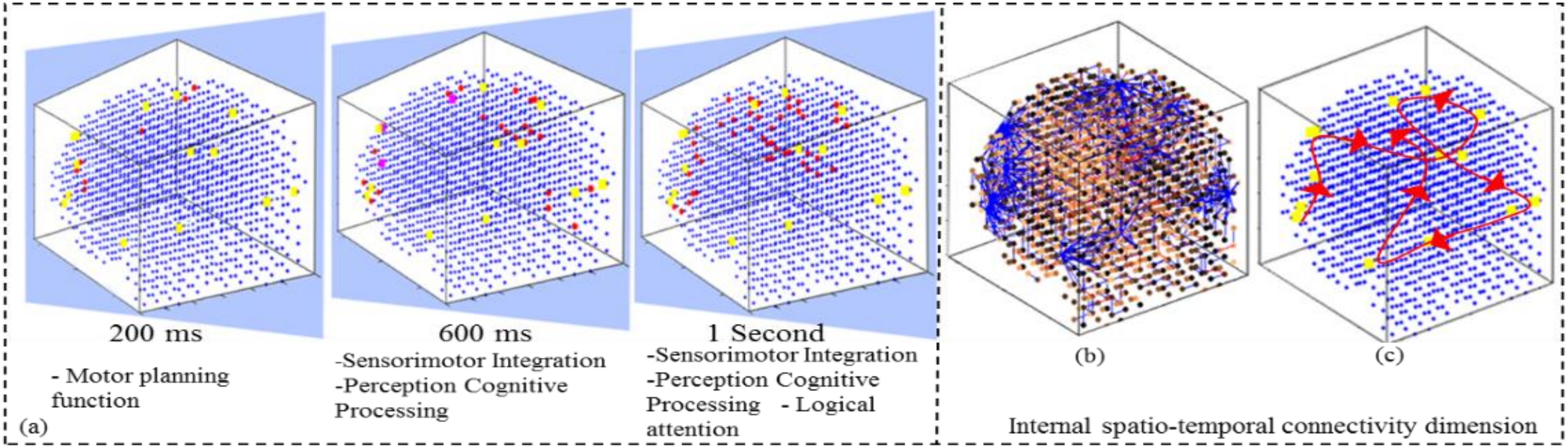
Anatomical locations of international 10–10 cortical projections

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

KEDRI

Example

A SNNcube that learns EEG data from 14 EEG channels when a person is moving a hand. 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

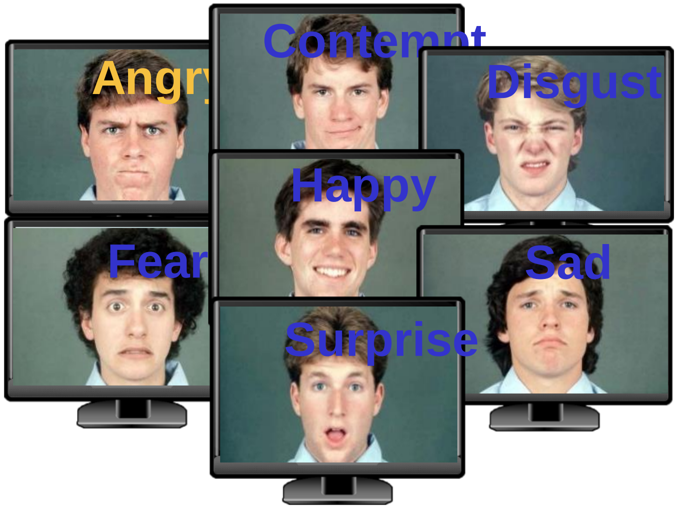
AND E3: Perception, in the Perception Cognitive brain area, time T3

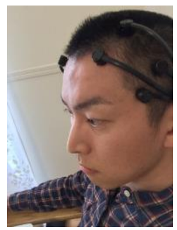
AND E4: Attention, in the Logical Attention brain area, time T4.

Emotional facial expression recognition and facial expression production

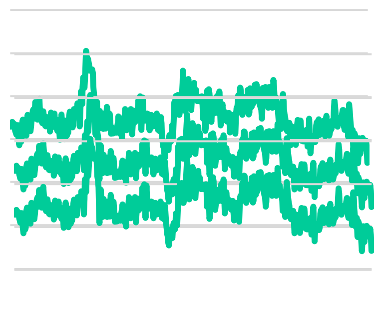
(H.Kawano, Z.Doborjeh, N.Kasabov, Proc. ICONIP 2016, Kyoto, 2016)

Facial Expression Perception Task

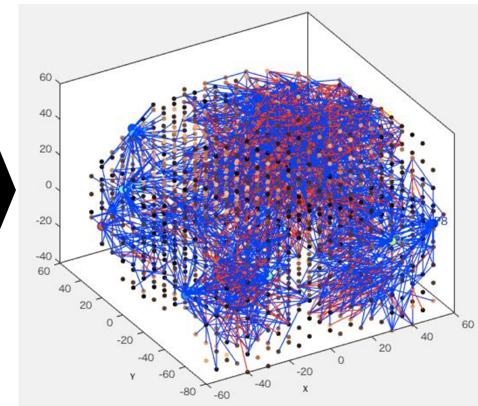




14ch EEG



94.3 %

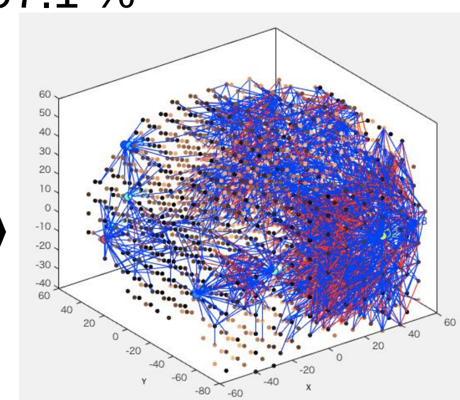


Face Expression Production Task

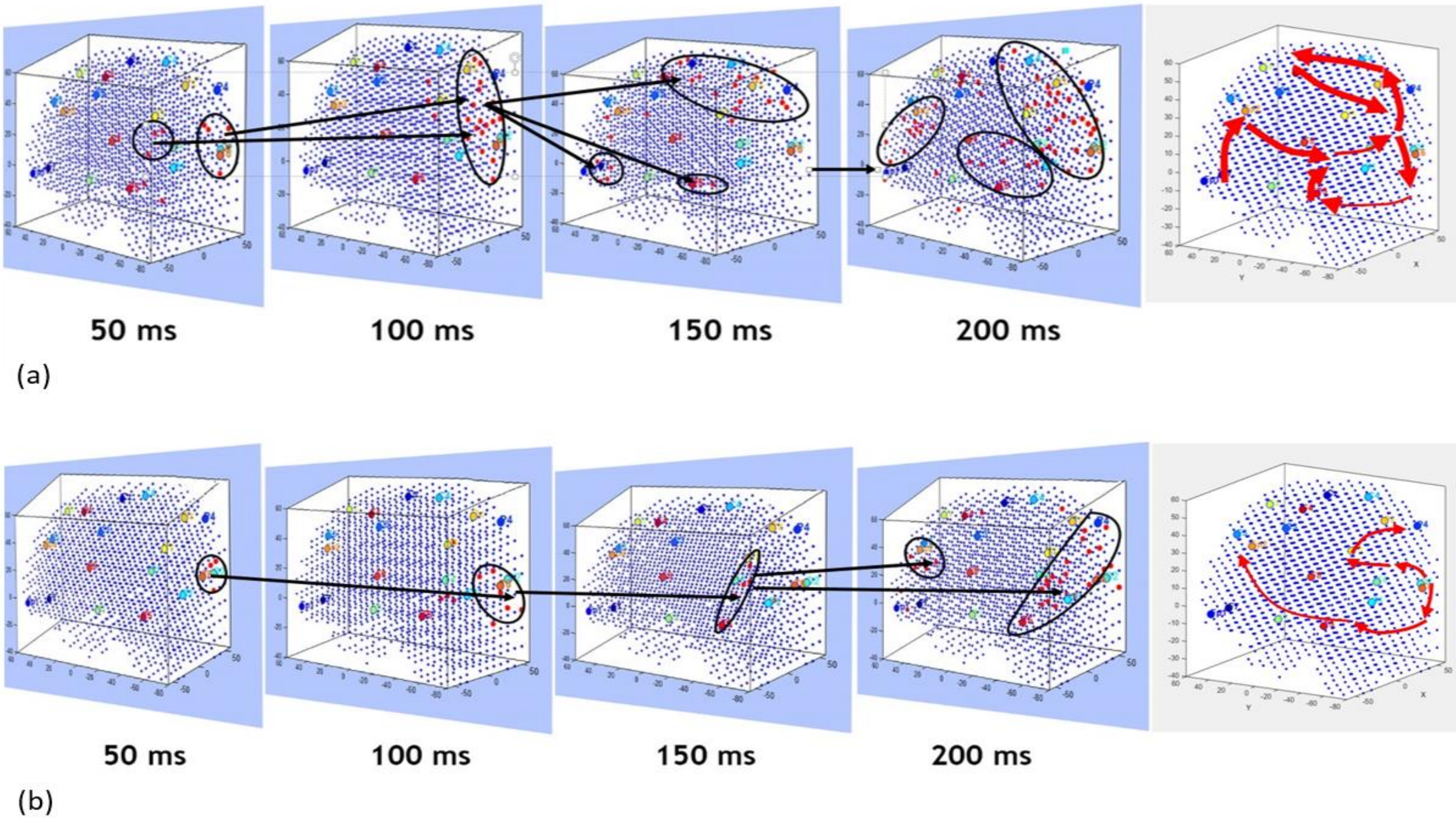
14ch EEG

97.1 %

NeuCube



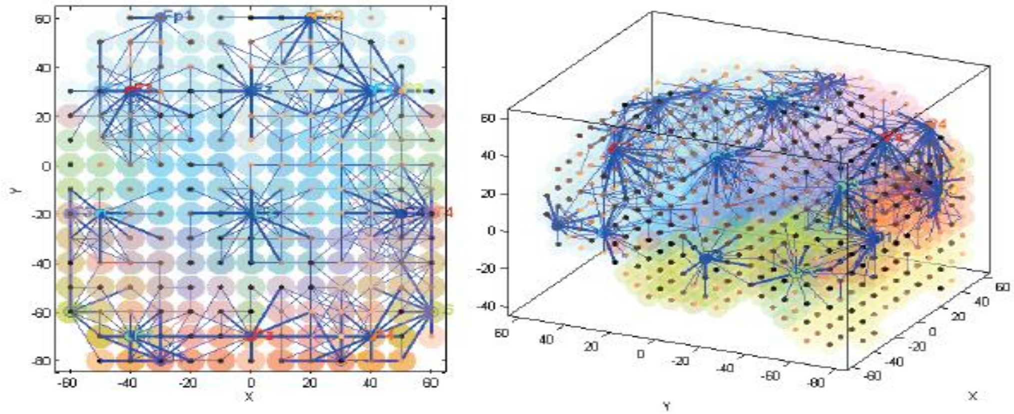
Tracing the brain dynamics in a NeuCube model



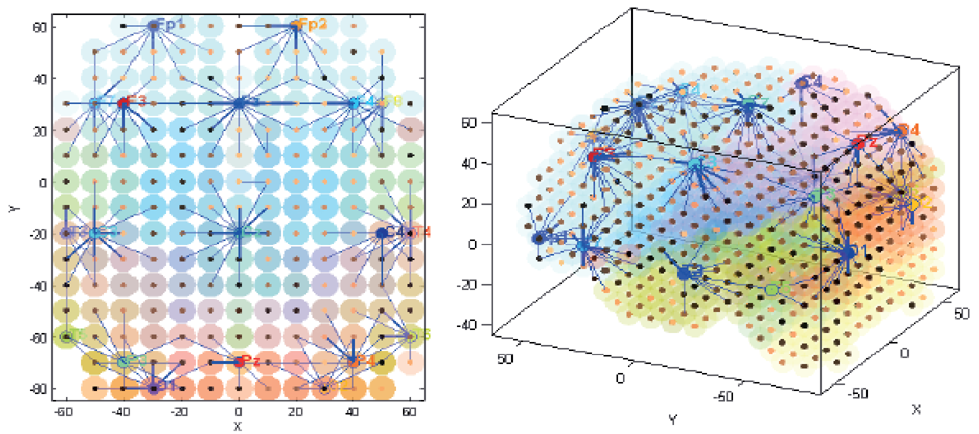
Z.Doborjeh, N. Kasabov, M. Doborjeh & Alexander Sumich**,** Modelling Peri-Perceptual Brain Processes in a Deep Learning Spiking Neural Network Architecture, ***Nature,*** Scientific REPORTS | (2018) 8:8912 | DOI:10.1038/s41598-018-27169-8; https://www.nature.com/articles/s41598-018-27169-8

Applications of EEG data modelling (Ch9)
Predicting progression of MCI to AD

E.Capecci, Z.Doborjeh, N.Mammone, F. La Foresta, F.C. Morabito and N. Kasabov, Longitudinal Study of Alzheimer's Disease Degeneration through EEG Data Analysis with a NeuCube Spiking Neural Network Model, Proc. WCCI - IJCNN 2016, Vancouver, 24-29.07.2016, IEEE Press.



(a) EEG signal collected at t_0.

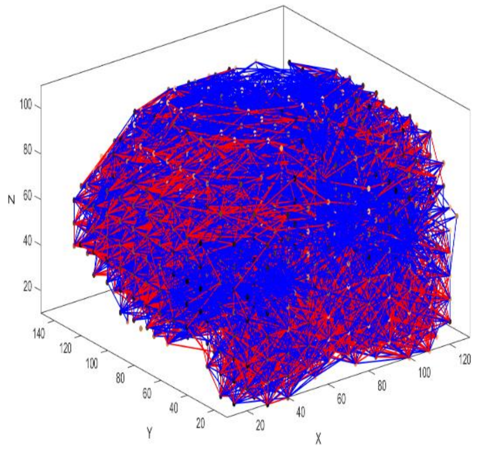
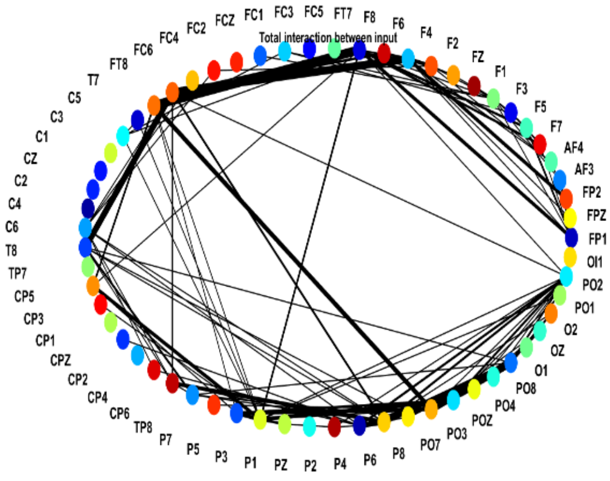


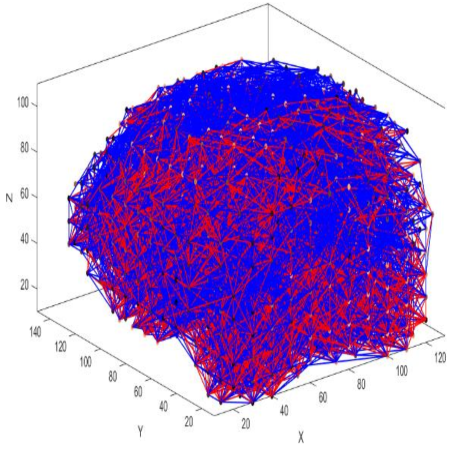
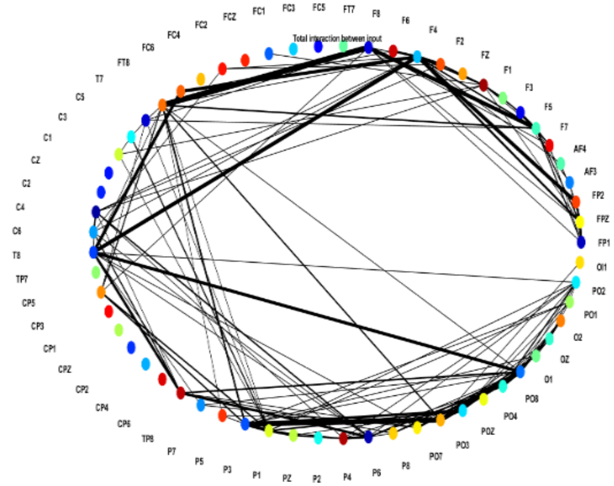
(b) EEG signal collected at t_1.

Brain disease diagnosis and prognosis based on EEG data

D Shah, G Wang, M Doborjeh, Z Doborjeh, N Kasabov, ICONIP 2019, Sydney 12-15.12.2019

Learning and representation of EEG data for a better understanding of depression,

Visualization for eyes open state:

(a) NeuCube connectivity and FIN when a system is trained on only on depressed subjects EEG data;

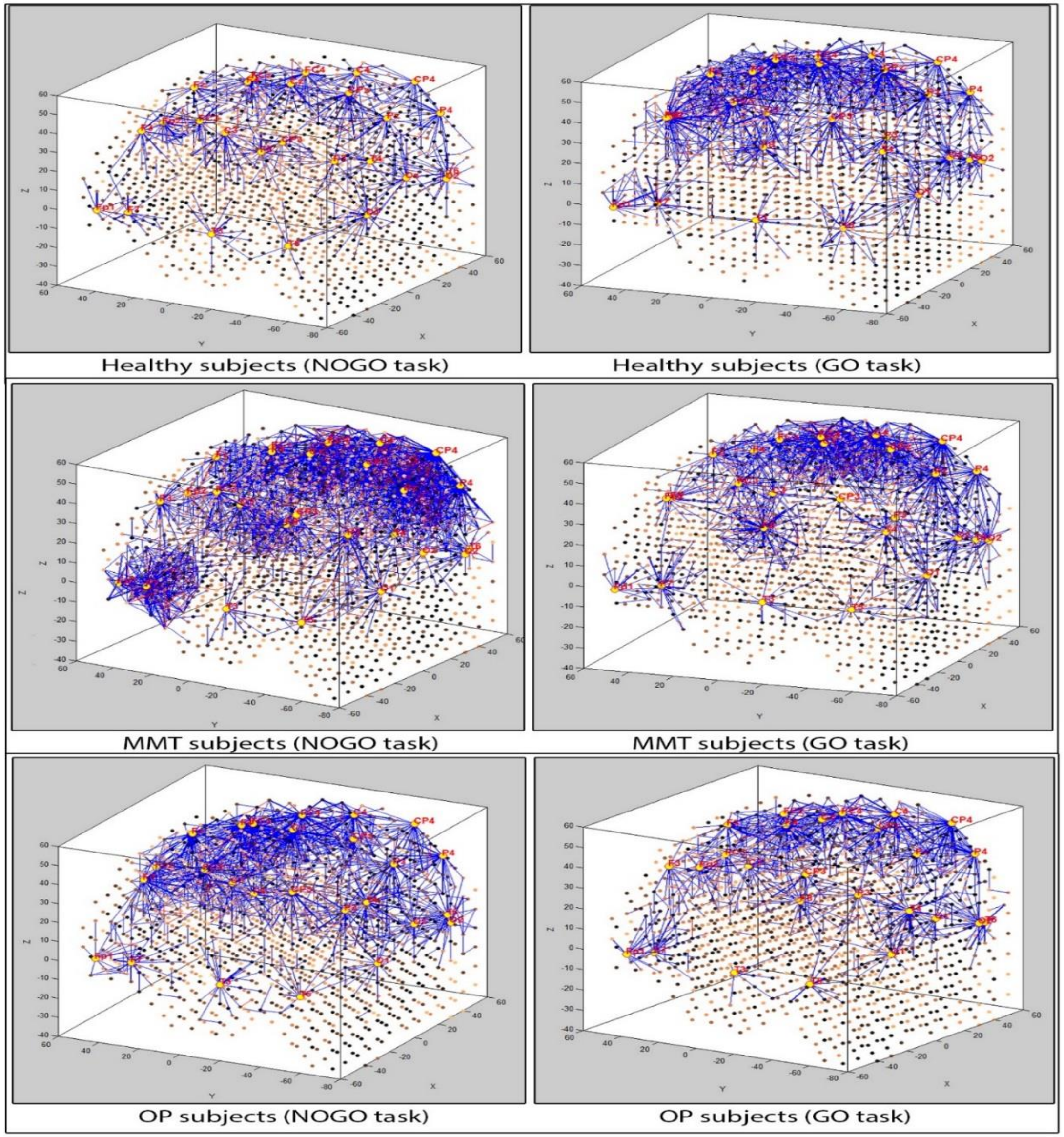
(b) NeuCube connectivity and FIN when a systems is trained only on healthy subjects data.

Findings/knowledge discovered

- A strong interaction F4-T8-PO8 across the right hemisphere in the healthy group is absent in the depressed group.
- There are more right frontal interactions in the depressed group including F4, F6, F8, FC4, FC6, and FC8 as compared to the healthy group indicating more negative perception in the brain.
- Long-range interaction between FT8-PO7 and F8-P1 in the depressed group.

Understanding and predicting addicts' response to treatment

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



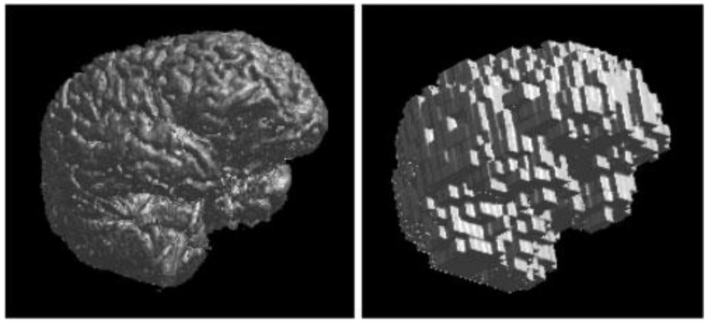
Tracing and interpreting dynamic brain activities in the GO/NOGO task performed by three subject groups:

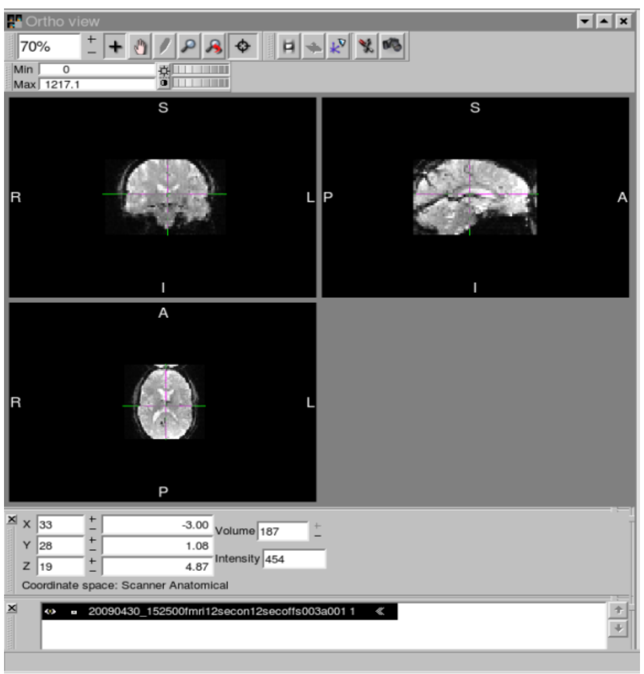
- healthy subjects CO);

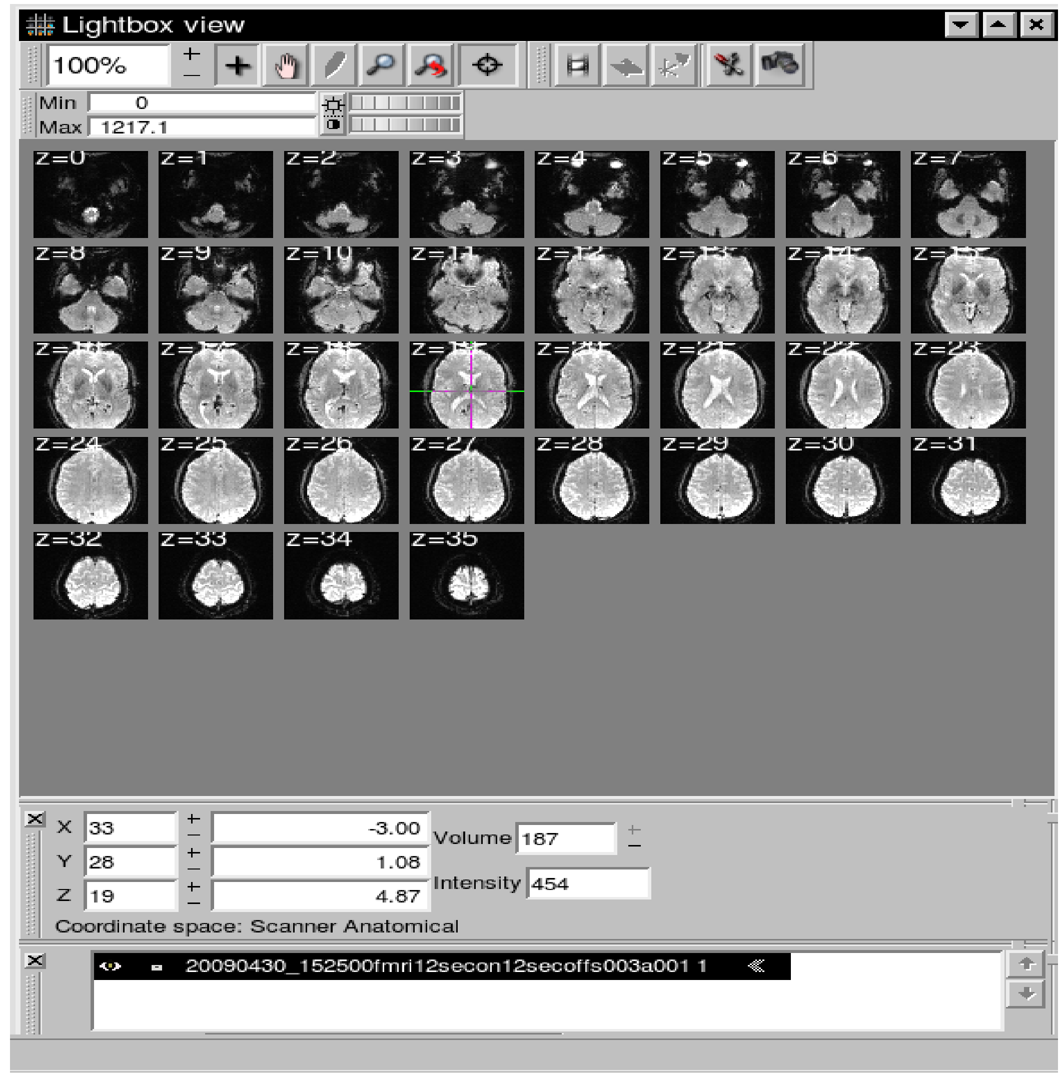
- addicts on Methadone treatment (MMT);

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

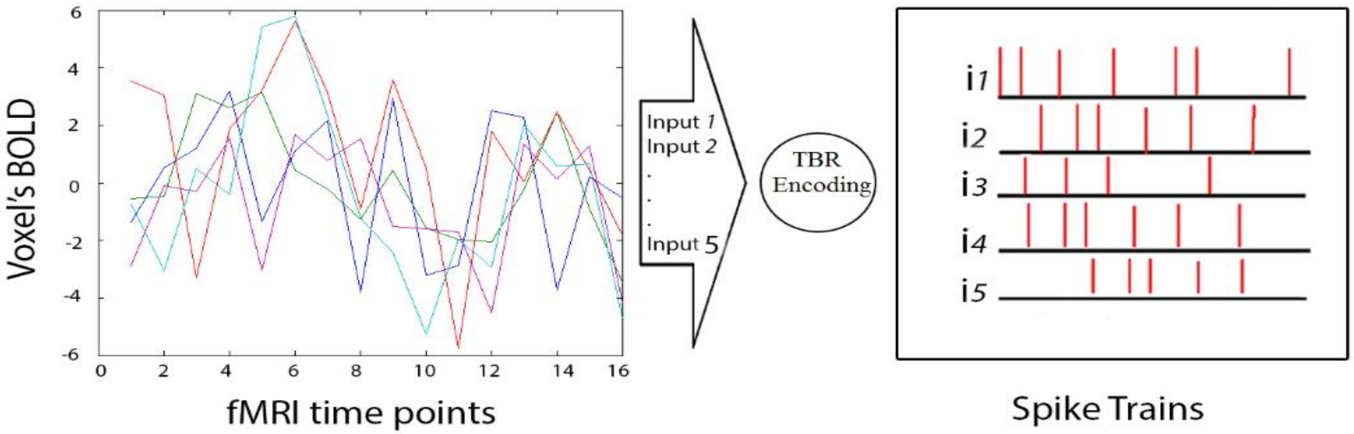
What are fMRI brain signals? (Ch.10)

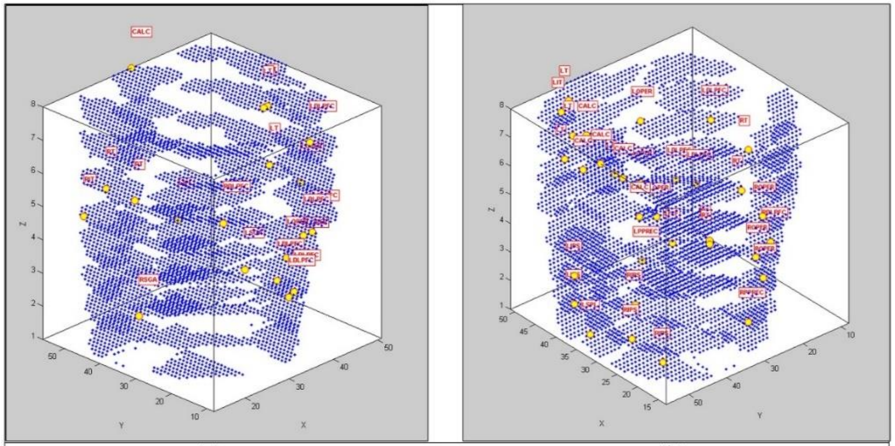




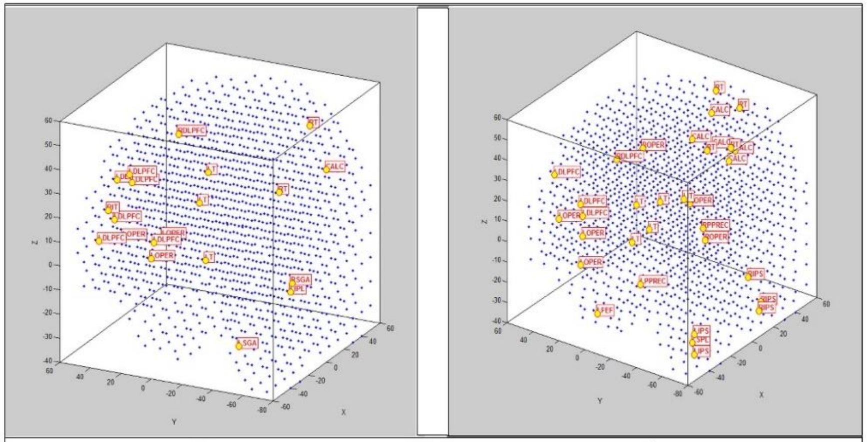


Encoding fMRI data into spikes and mapping them into NeuCube





(a) (b)

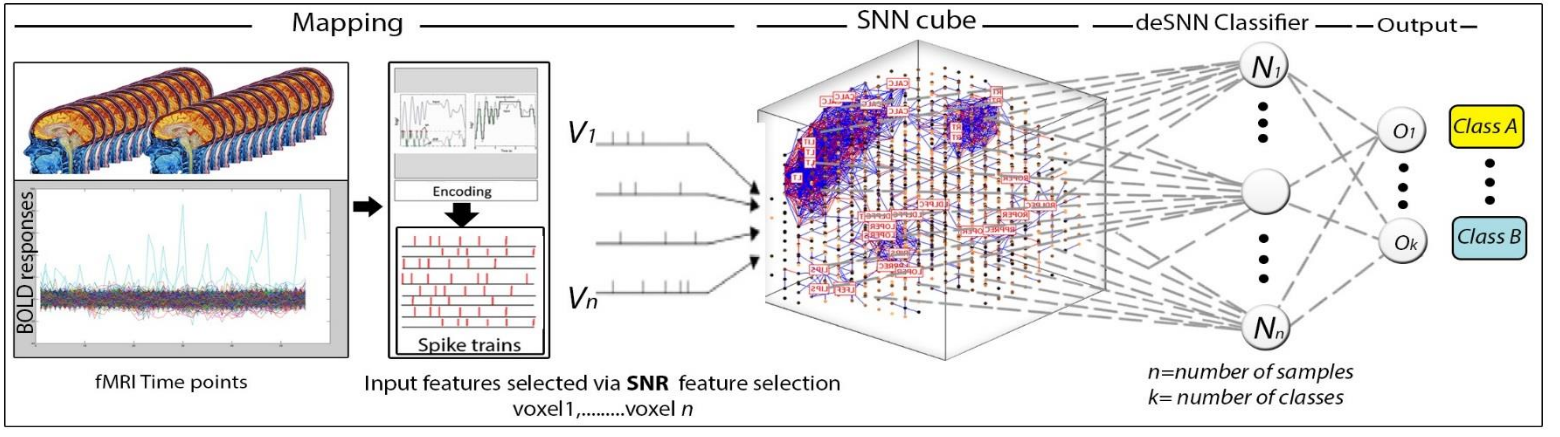


(a) (b)

Deep learning and deep knowledge representation of fMRI data (Ch.10)

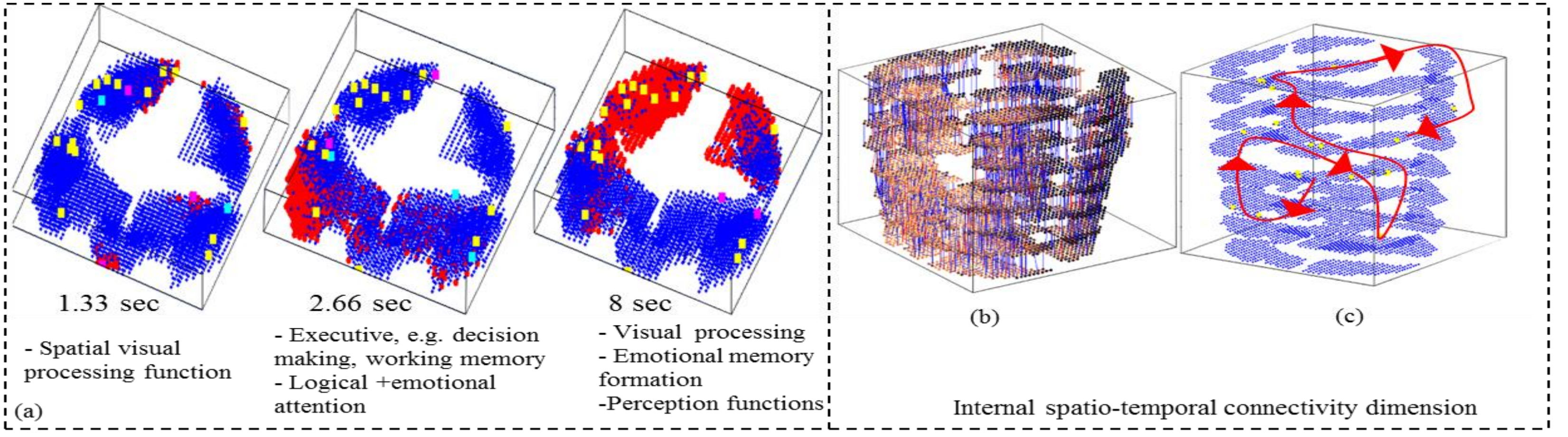
(Spatial mapping of fMRI voxels into a 3D SNN cube after conversion into Talairach coordinates.

N.Kasabov, M.Doborjeh, Z.Doborjeh, IEEE Transactions of Neural Networks and Learning Systems, DOI: 10.1109/TNNLS.2016.2612890,2016



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

NeuCube for learning and knowledge representation of cognitive fMRI



Only three snapshots of learning of 8-second fMRI data in a NeuCube model when a subject is reading a negative sentence (time is in seconds) (the left 3 figures); Internal structural pattern represented as spatio-temporal connectivity in the SNN model trained with 8-second fMRI data stream; a functional pattern represented as a sequence of spiking activity of clusters of spiking neurons in a trained NeuCube model (the right most figure).

TSK representation extracted from a trained SNN model related to modelling fMRI data when a person is reading a negative sentence

IF (a person is reading a negative sentence)

THEN (the following events are triggered in space and time in a trained SNN model)

E1: Vision, in the Spatial Visual Processing area, at time T1,

AND E2: Decision making function, in the Decision making and working memory, at time T2,

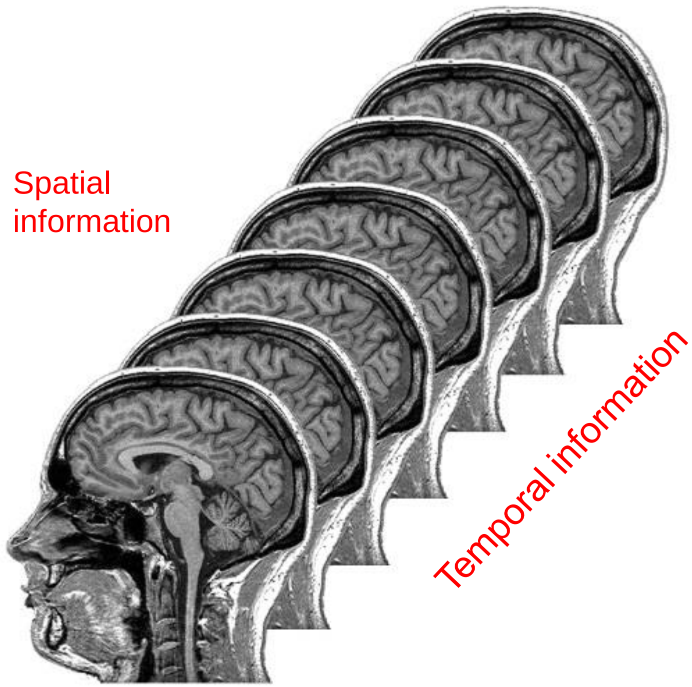
AND E3: Logical and Emotional Attention function, in the Attentional brain area, at time T3

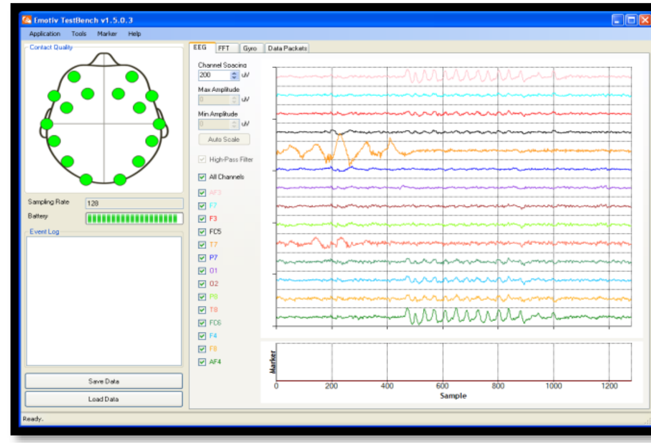
AND E4: Emotional functions, in the Emotional brain area, at time T4

AND E5: Emotional memory formation function, in the Memory brain area, at time T5

AND E6: Perception function, Perception brain area, at time T6.

Integrating fMRI and EEG – a challenge





Modelling simultaneously EEG and fMRI data is an open problem:
- different time scales
- different spatial resolution

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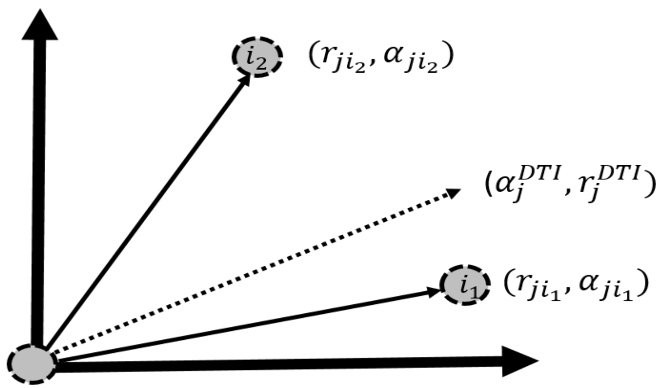
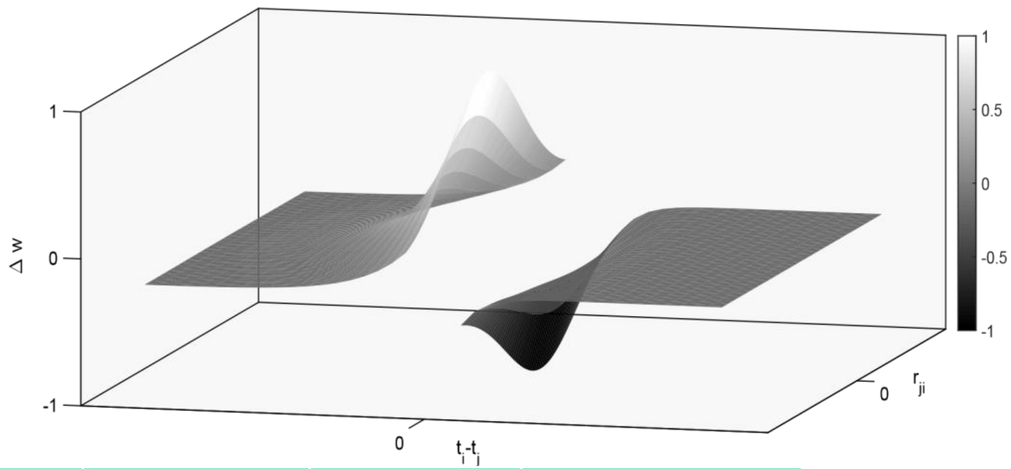
Deep learning of time-, space- and orientation data (Ch11)

A case study on fMRI and DTI brain data





Method	Data	Temporal	Multi-dimensional	Accuracy(%)	Cohen's κ
BSA+oiSTDP+KNN	fMRI+DTI	yes	Yes	**72.3±12.3**	0.44±0.25
BSA+STDP+KNN	fMRI	Yes	no	69.4±13.9	0.38±0.28
BSA+KNN	fMRI	no	No	64.2±12.4	0.22±0.26
Sparse Autoencoder [45]+KNN(E) [44]	fMRI	No	no	56.1±7.2	0.01±0.11
PCA [44]+KNN(E) [44]	fMRI	no	No	56.1±11.3	0.13±0.18
ICA [44]+KNN(E) [44]	fMRI	no	No	62.8±12.3	0.26±0.23
RBM [44]+KNN(E) [44]	fMRI	no	no	36.2±4.9	−0.23±0.11
LSTM [45]	fMRI	yes	no	45.7±9.6	−0.15±0.14
GRU [45]	fMRI	yes	no	45.2±7.5	−0.018±0.13

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

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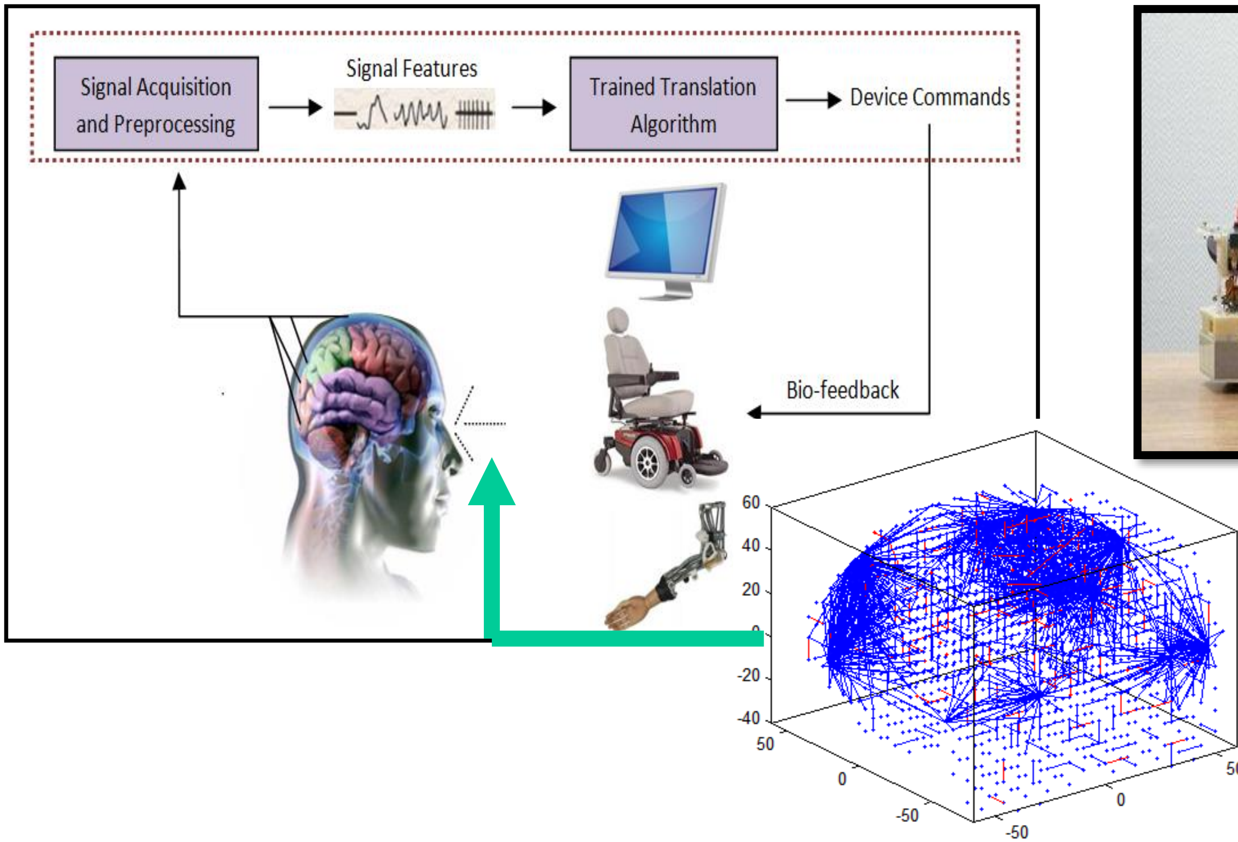
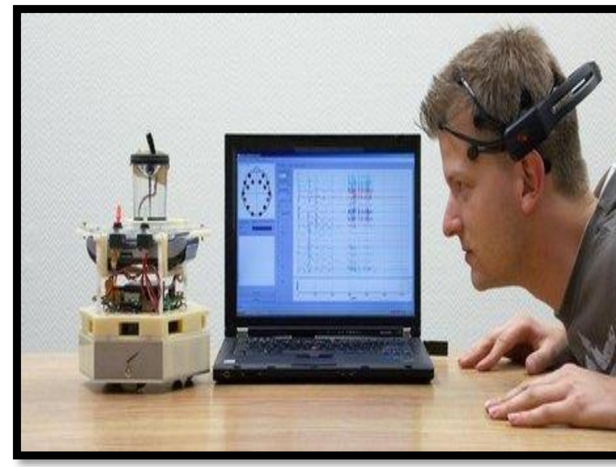
Lecture 13. Brain Computer Interfaces (Ch.14)

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.

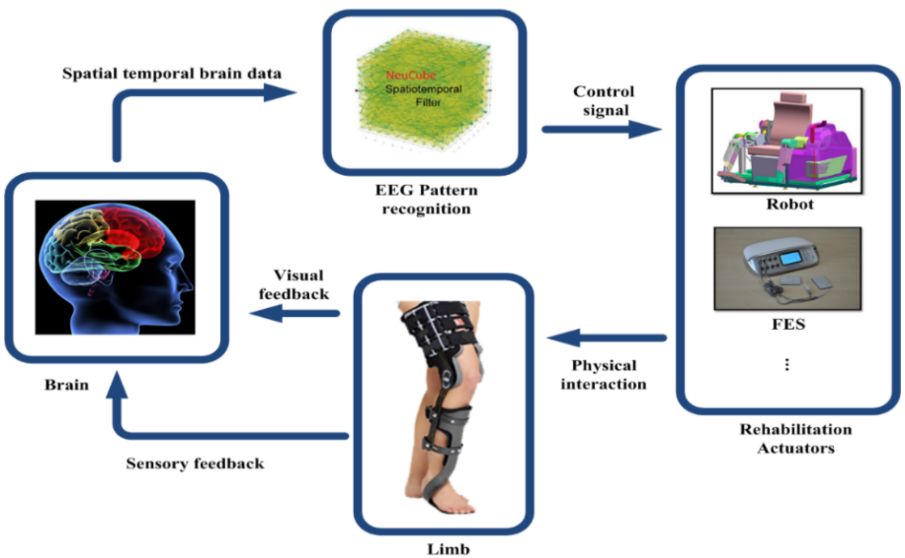


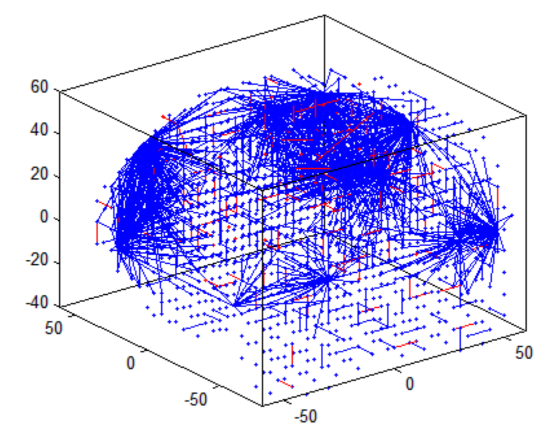


BI-SNN for neurorehabilitation

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

1. D. Taylor, N.Scott, N. Kasabov, E.Capecci, E. Tu, N. Saywell, Y. Chen, J.Hu and Z.Hou, Feasibility of NeuCube SNN architecture for detecting motor execution and motor intention for use in BCI applications, Proc. WCCI 2014, Beijing, 7-13 July 2014, IEEE Press.
2. Hu, J., Hou, Z., Chen, Y., Kasabov, N., & Scott, N. (2014). EEG-Based Classification of Upper-Limb ADL Using SNN for Active Robotic Rehabilitation. In 2014 5th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (pp. 409-414). Sao Paolo, Brazil: IEEE. doi:10.1109/BIOROB.2014.6913811
3. N. Kasabov, J.Hu, Y. Chen, N.Scott, and Y. Turkova, Spatio-temporal EEG data classification in the NeuCube 3D SNN Environment: Methodology and Examples, Proc. ICONIP 2013, Springer LNCS, vol.8228, pp.63-69.
4. Y.Chen, J.Hu, N.Kasabov, Z. Hou and L.Cheng, NeuroCubeRehab: A Pilot Study for EEG Classification in Rehabilitation Practice Based on Spiking Neural Networks, Proc. ICONIP 2013, Springer LNCS, vol.8228, pp.70-77.





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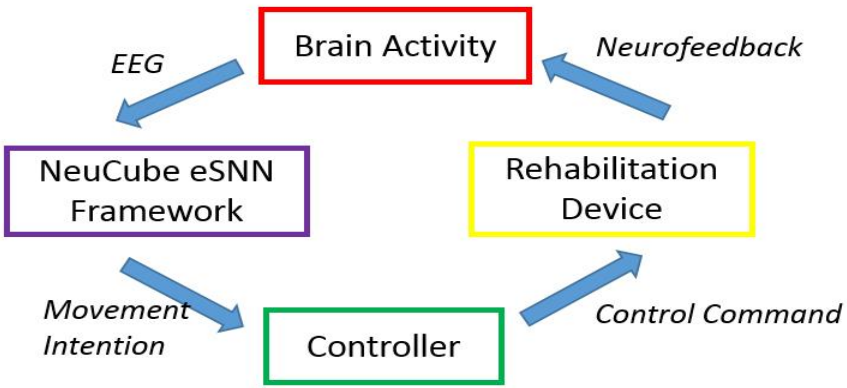
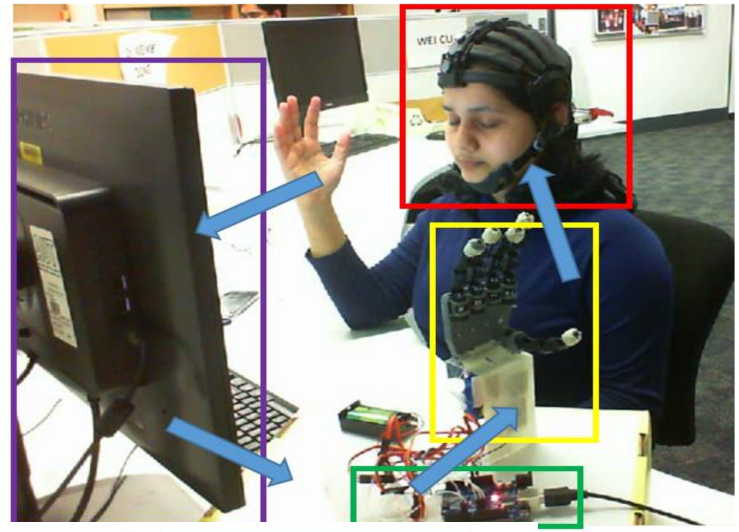
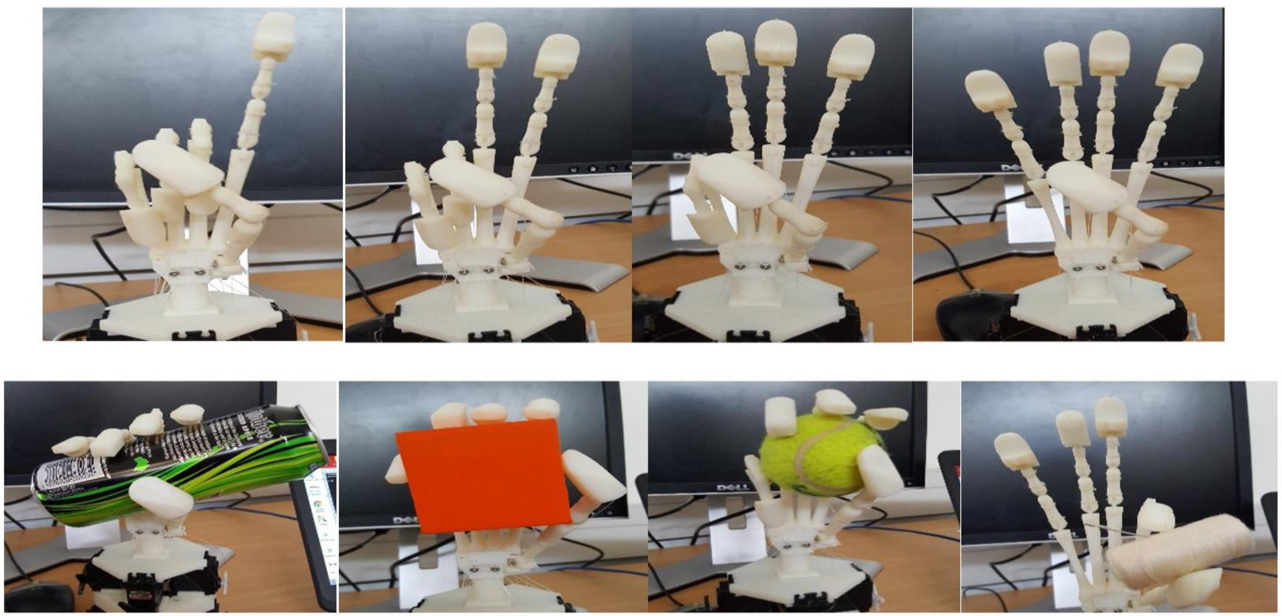
NeuCube for BCI with neurofeedback for prosthetic hands

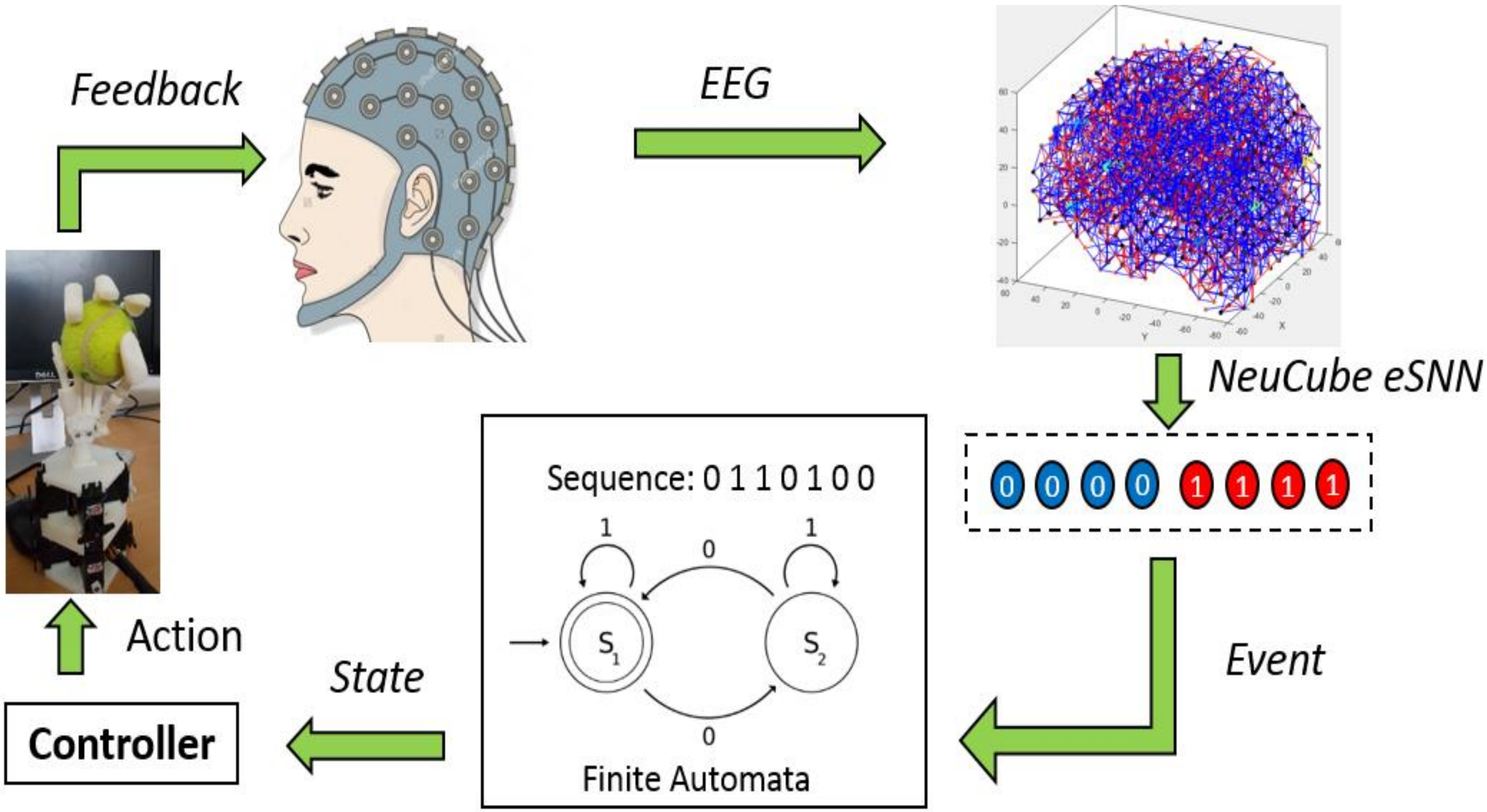




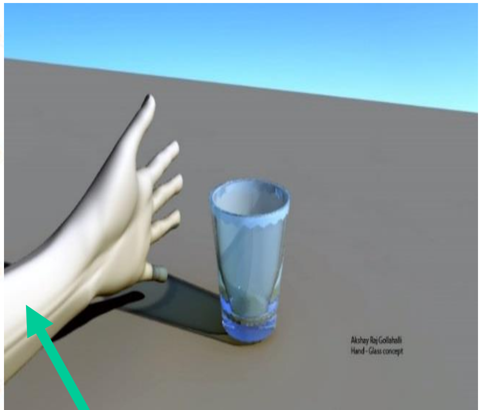


FaNeuRobot: A Brain-Like Motor Controlling Framework for Prosthetic Control using Automata Theory, Cognitive Computing & NeuCube Evolving Spiking Neural Network Architecture

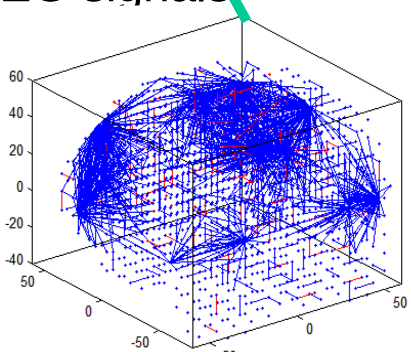
K. Kumarasinghe, M. Owen, N. Kasabov, D. Taylor, Chi Kit Au, Proc. IEEE Robotics Conference, Sydney, May 2018.



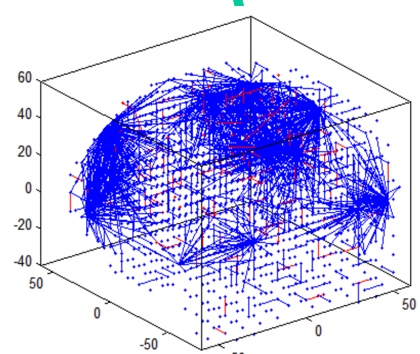
Learning and understanding brain-computer (VR/AR) interaction in time-space



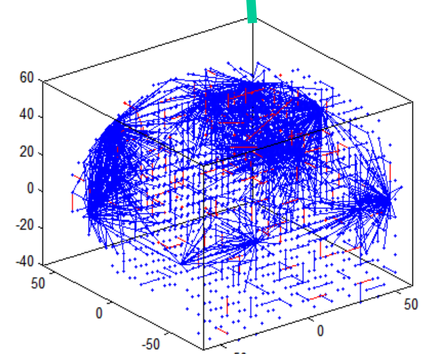
A prototype virtual environment of a hand attempting to grasp a glass controlled with EEG signals.



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.



Questions

1. Why do we need to model brain-data?
2. What is EEG data?
3. What is fMRI data?
4. Why do we need brain-computer interfaces?