Advanced Artificial Intelligence Technologies and Applications

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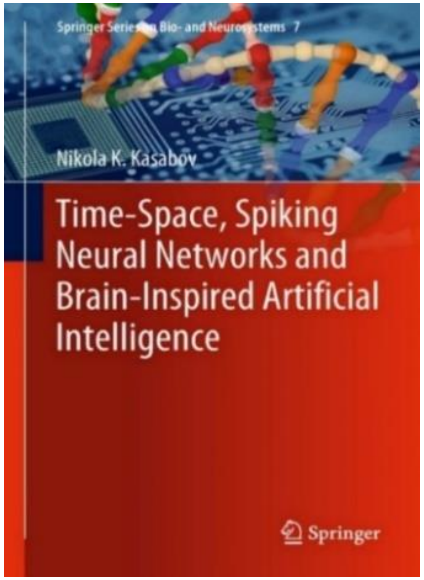
Full course DLU, 2023, Lecture Content

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. Evolutionary and quantum inspired computation (Ch.7)
10. AI applications in health (Ch.8-11)
11. AI applications for computer vision (Ch.12,13)
12. AI for brain-computer interfaces (BCI) (Ch.14)
13. AI for language modelling. ChatBots (extra reading)
14. AI in bioinformatics and neuroinformatics (Ch15,16, 17,18)
15. AI applications for multisensory environmental data (Ch.19)
16. AI in finance and economics (Ch19)
17. Neuromorphic hardware and neurocomputers (Ch20).



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

N. Kasabov Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1996.
ZOOM link for all lectures: https://us05web.zoom.us/j/4658730662?pwd=eFN0eHRCN3o4K0FaZ0lqQmN1UUgydz09

Lecture 6.

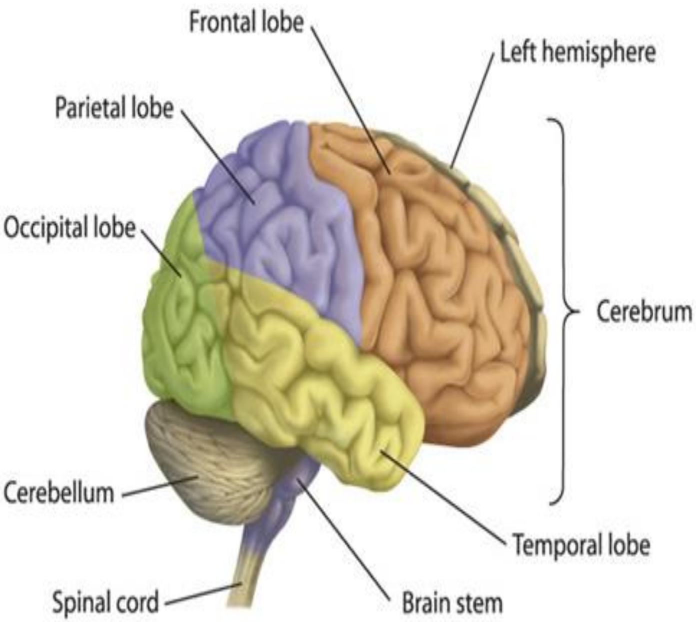
Deep learning and deep knowledge representation in the human brain (Ch3)

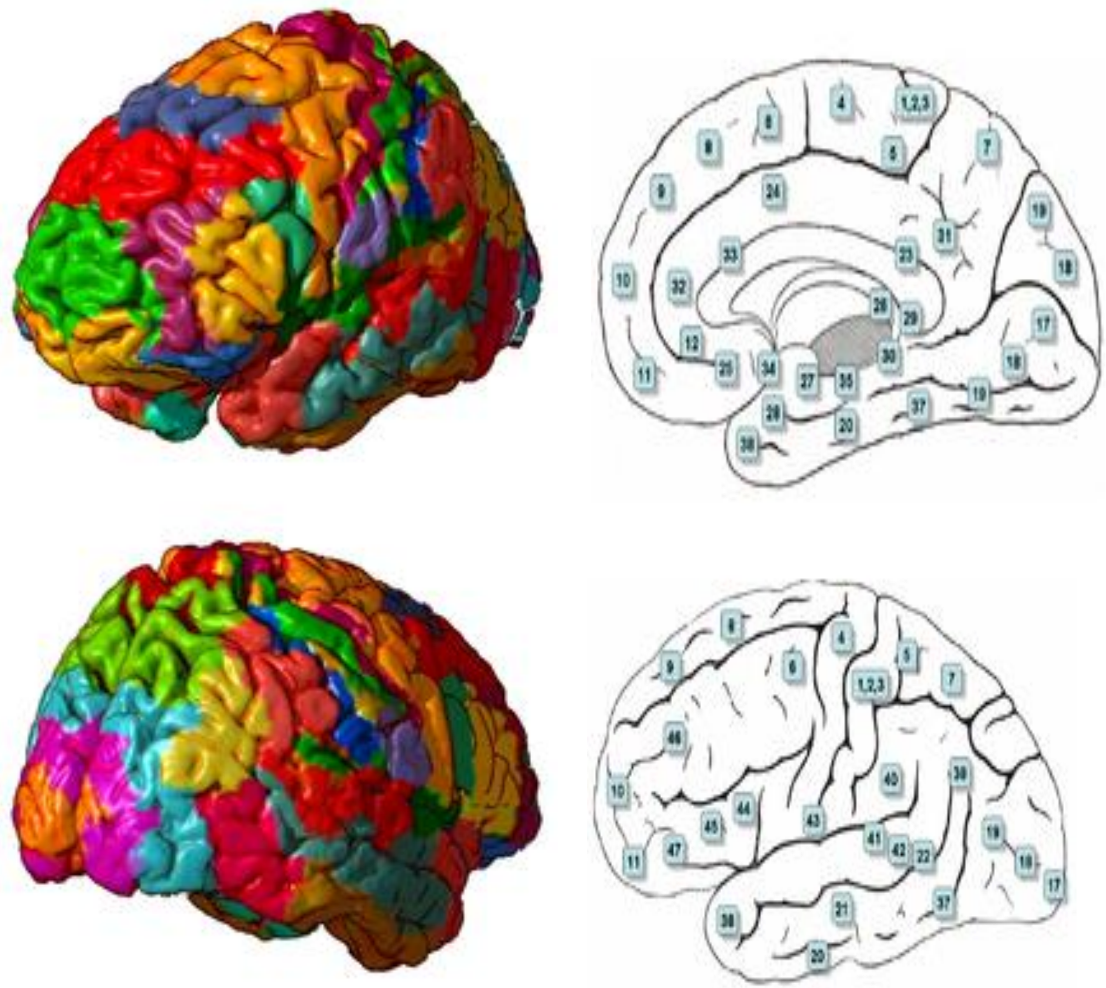
1. Why do we need to study the human brain?
2. Spatio-temporal organisation of the human brain
3. Learning and memory
4. Signal processing in the brain
5. Brain data
6. Questions for individual work

1. Why do we need to study the human brain?

1. To understand principles of learning, memory and languages
2. To use these principles for the creation of better BI-AI systems
3. To understand human vision and develop better BI-AI computer vision systems
4. To understand human hearing and develop better BI-AI speech recognition systems
5. To understand motor control in the brain for better BI-AI robotic systems
6. To use the above technologies (e.g. BCI) to help humans with brain or movement problems.
7. To use the above BI-AI technologies to prevent brain and other diseases (e.g. dementia, stroke, Alzheimer Disease, etc.),

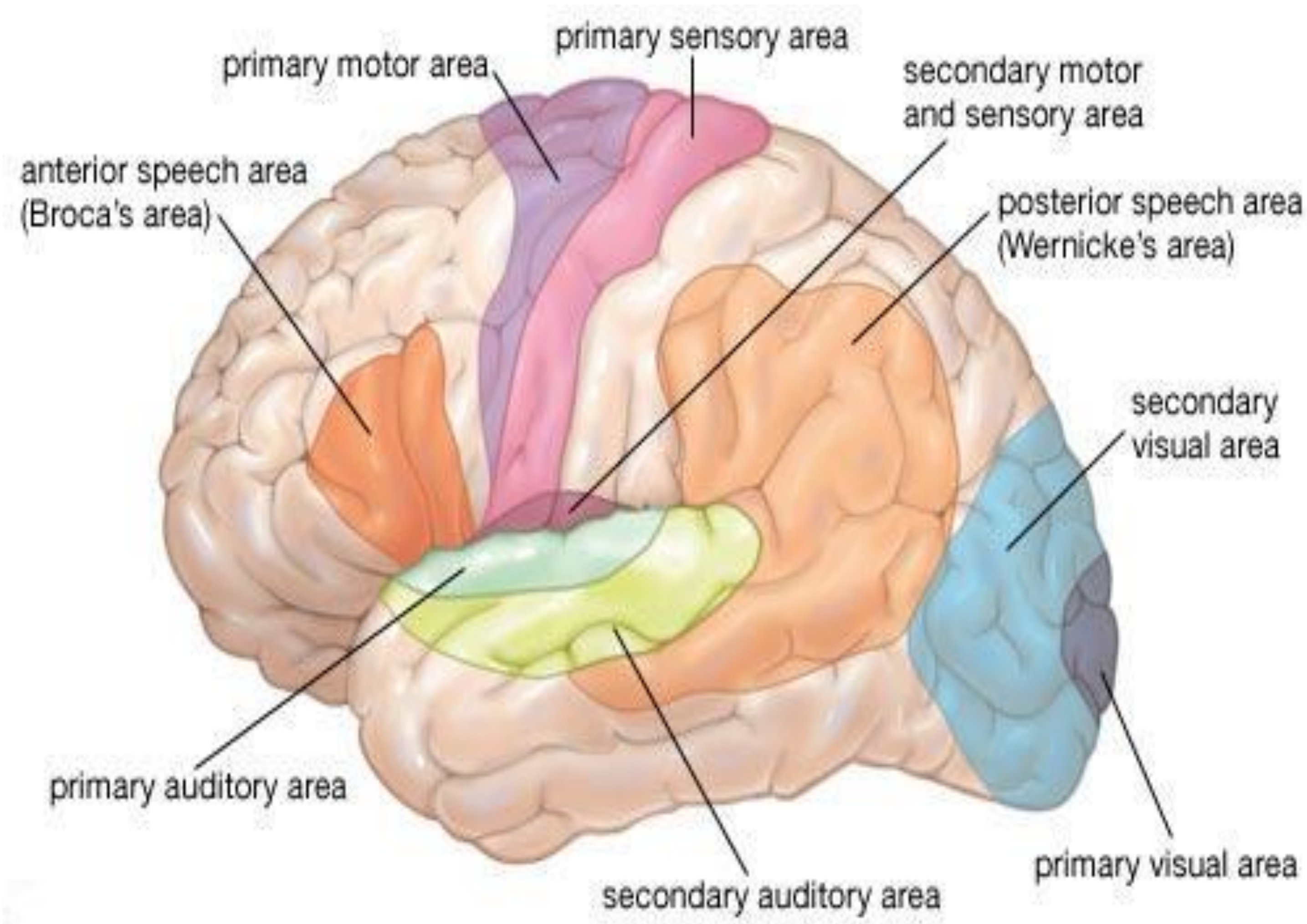
2. Spatio-temporal organisation of the human brain

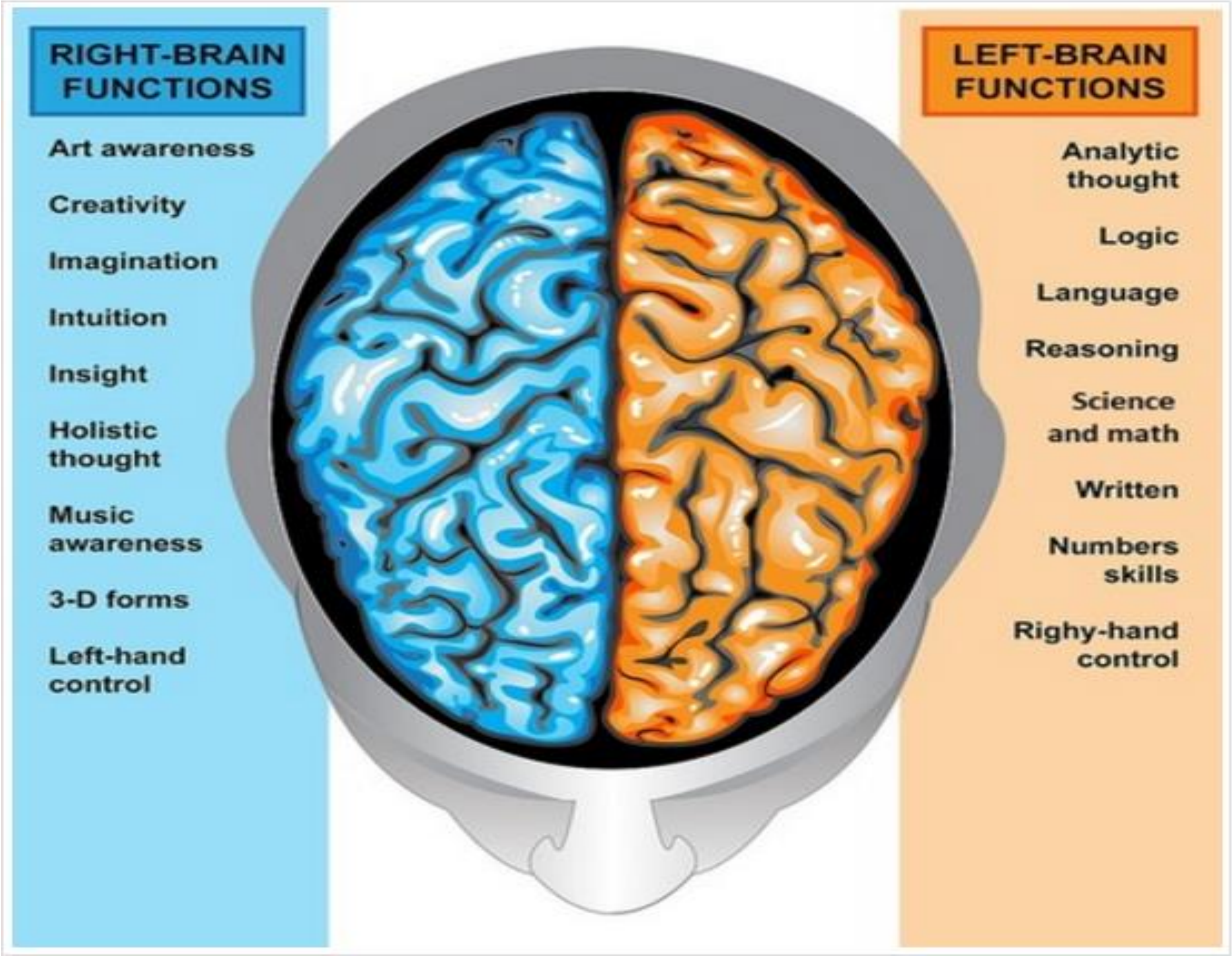




(Brodmann areas)

Different parts of the brain control different functions





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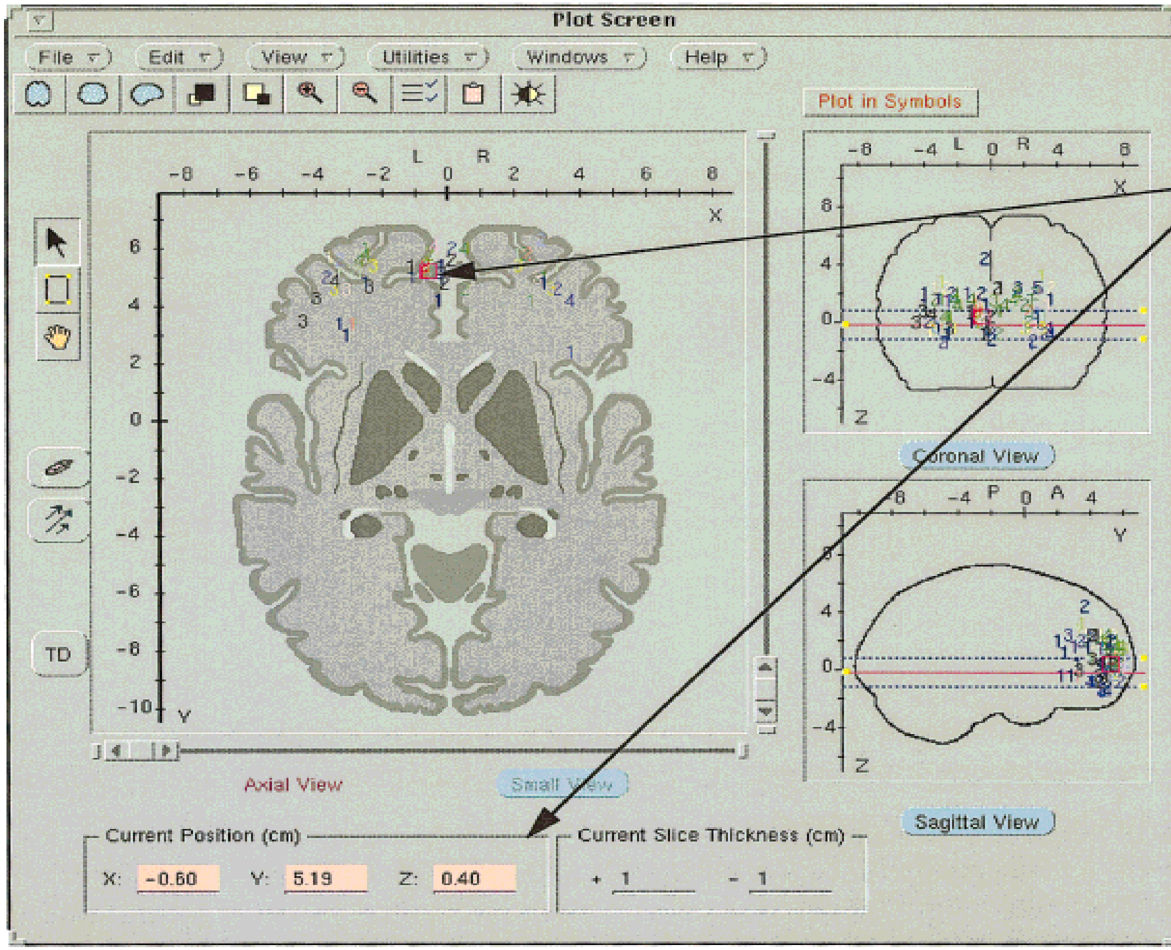
Brain Atlases: Brain spatial information

Talairach Atlas – Talairach Daemon

http://www.talairach.org/daemon.html



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**

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3. **Learning and memory in the human brain**

It is always in time and space.

Multiple languages are learned as TL in evolving and overlapping brain areas (world.edu)

Learning in the brain: The process of learning new categories of data and tasks by partially utilising already learned categories/tasks in the neuronal connections and adjusting other connections.

Spatially evolved *overlapping* structures in time for learning new tasks (e.g. multiple languages evolve in overlapping brain areas)

Learning of temporal data at different time scales:

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

Learning of memory types :

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

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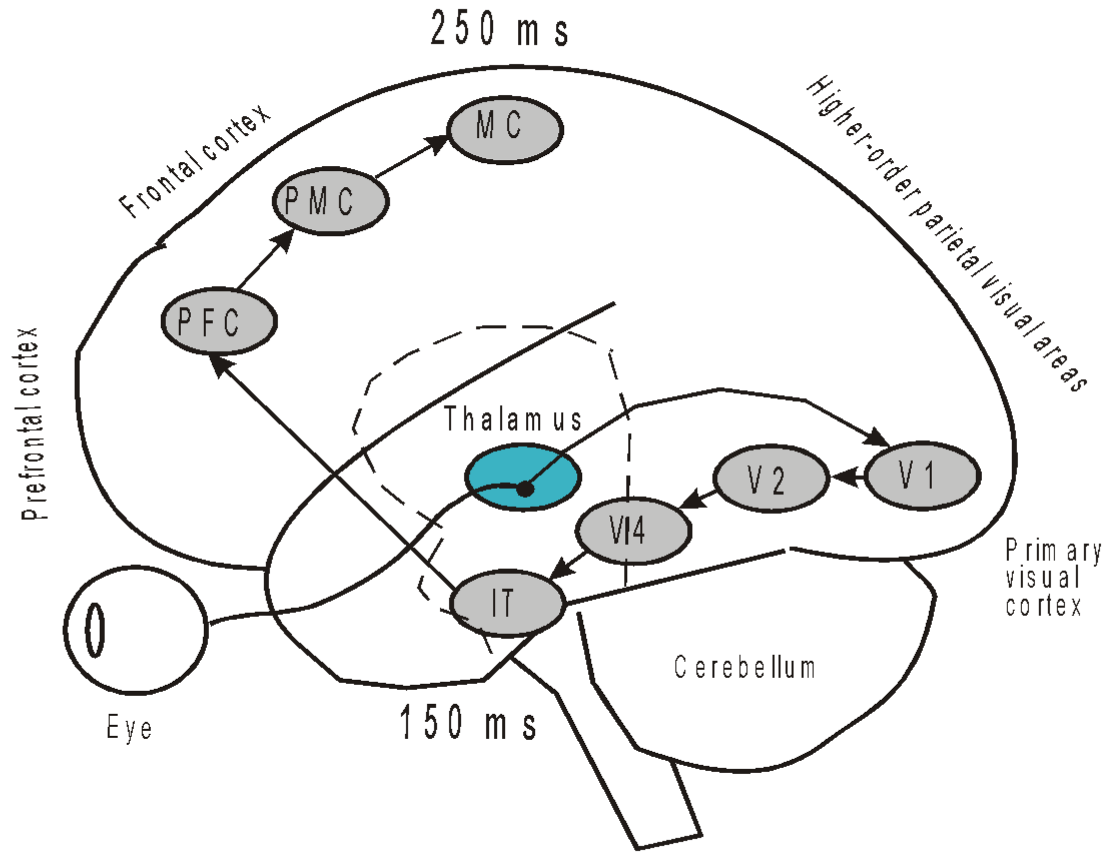
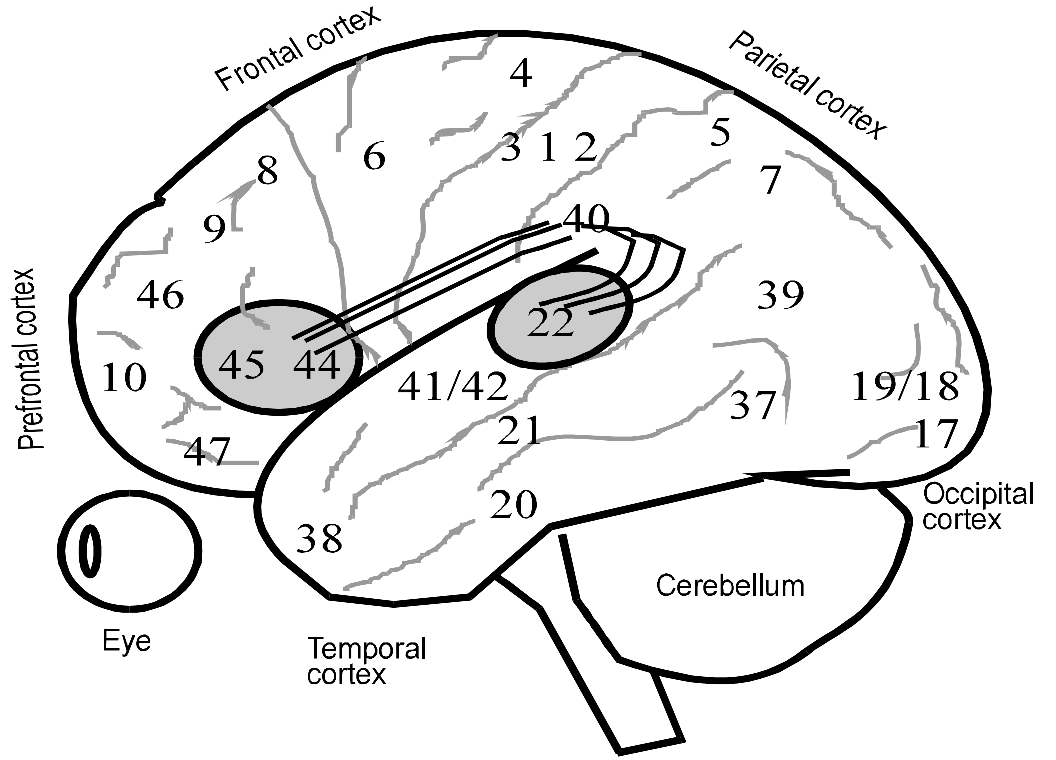
Learning to grasp an object



Example: A learned trajectory of activated neuronal clusters when a person has learned to see an object and to grasp it. When the person is learning to grasp another object, part of the already learned trajectory is used in a TL way (from (Benuskova and Kasabov, 2007).

Language learning and processing in time-space

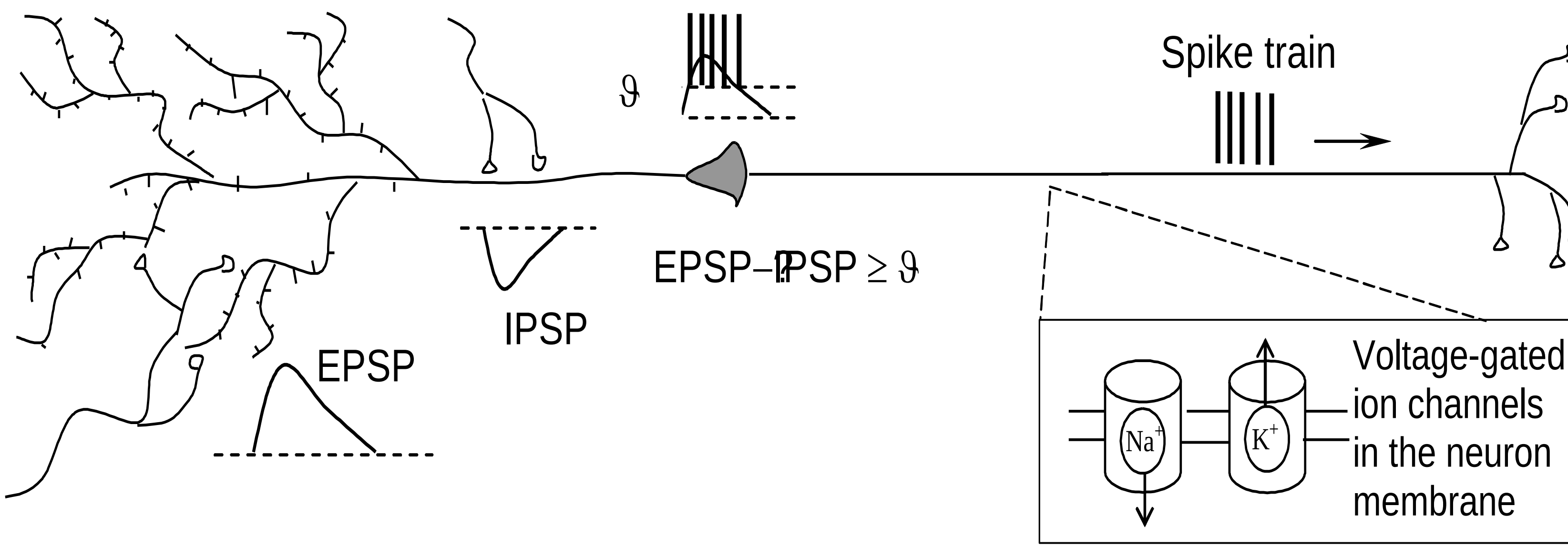


(from L.Benuskova, N.Kasabov, Computational neurogenetic modelling, Springer, 2007)

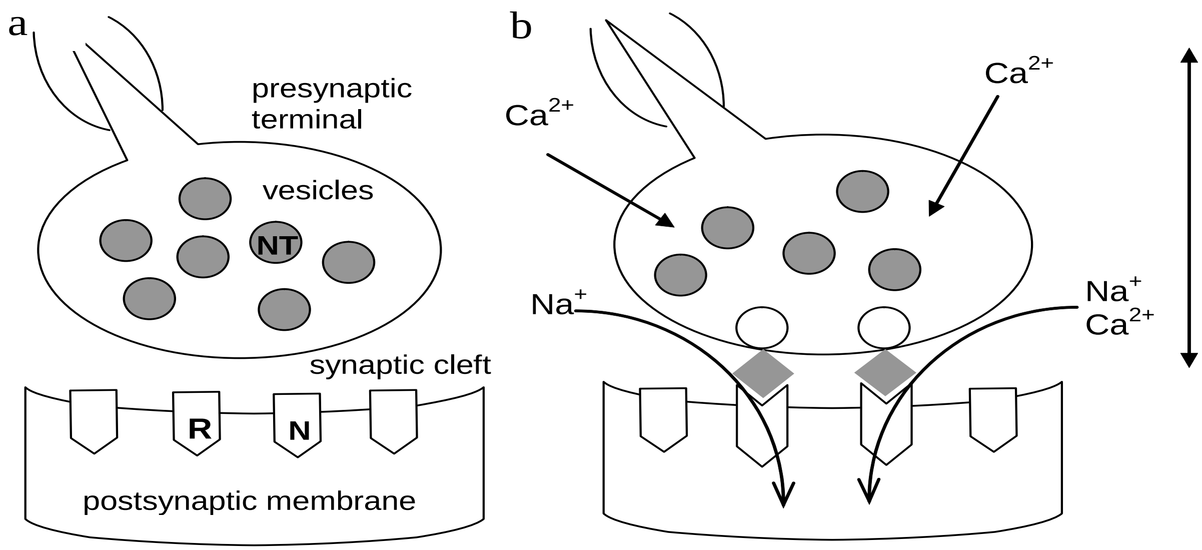
The basic model of language processing during the simple task of repeating the word that has been heard is the Wernicke-Geschwind model (Mayeux and Kandel 1991). A language task involves transfer of information from the inner ear through the auditory nucleus in thalamus to the primary auditory cortex (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.

4. **Signal processing in the brain**

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.



How does a synapse work?



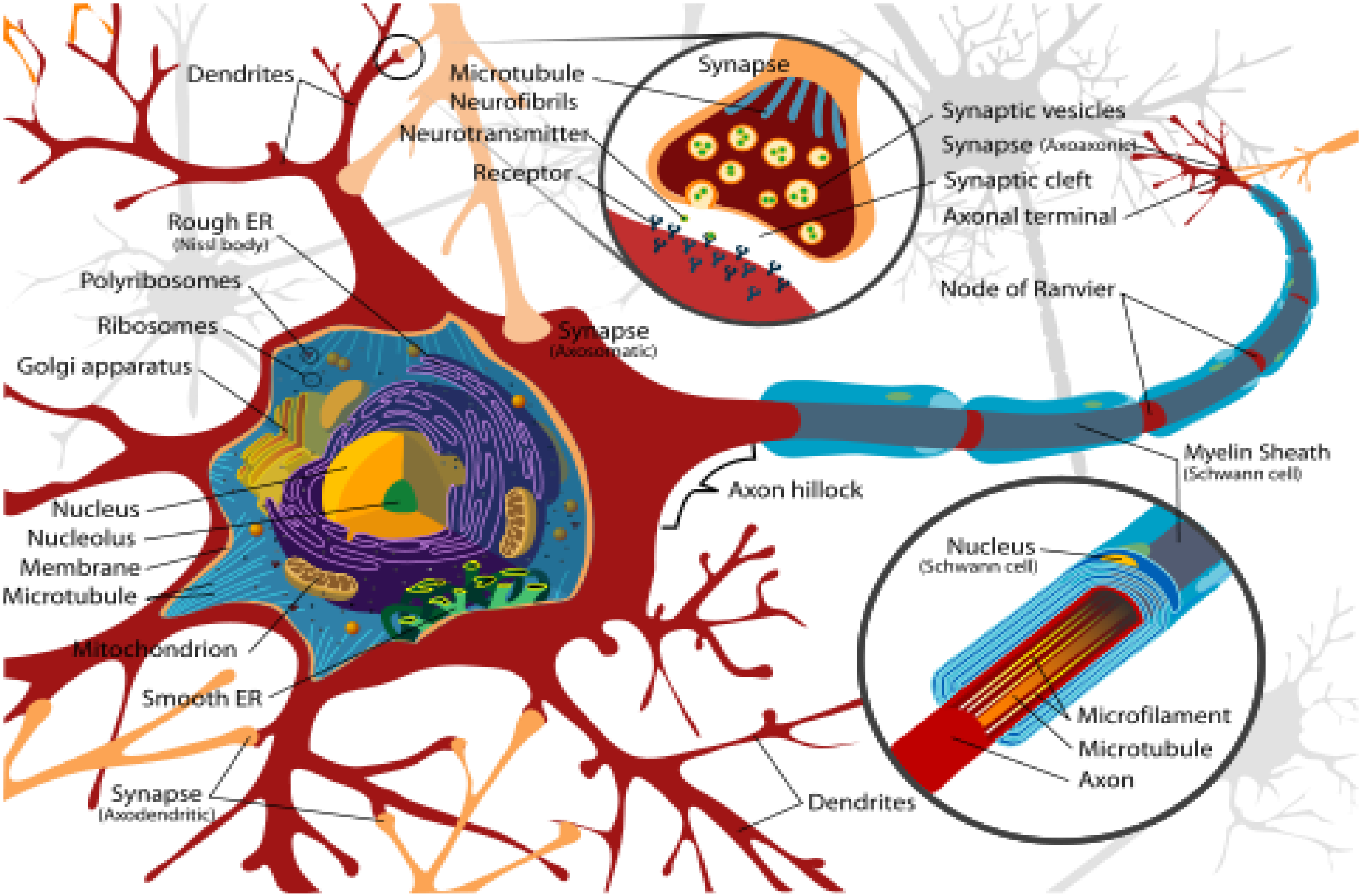
Abbreviation:

NT: neurotransmitter,

R : AMPA-receptor-gated ion channel for sodium,

N: NMDA-receptor-gated ion channel for sodium and calcium.

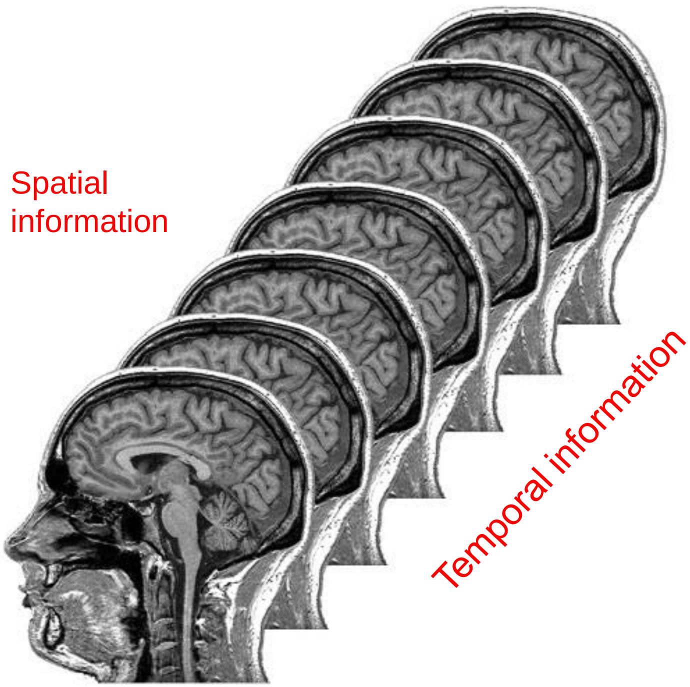
- Ion channels with quantum properties affect spiking activities in a stochastic way. “To spike or not to spike?” is a matter of *probability.*
- Transmission of electric signal in a chemical synapse upon arrival of action potential into the terminal is probabilistic
- Emission of a spike on the axon is also probabilistic
- Prior art on stochastic modelling of neuronal processes : D. Colguhoun, B. Sakmann, E. Neher, SShoman, SWang, DTank , JHopfield

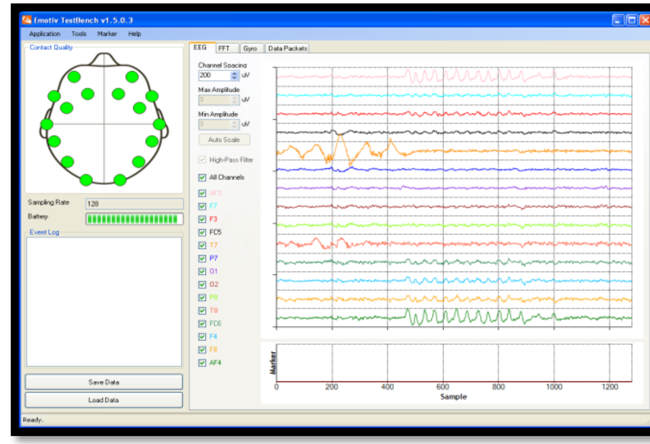

Dendrites
Microtubule
Neurofibrils
Neurotransmitter
Receptor
Synapse
Synaptic vesicles
Synapse (Axoaxonic)
Synaptic cleft
Axonal terminal
Rough ER
(Nissl body)
Polyribosomes
Ribosomes
Golgi apparatus
Synapse
(Axosomatic)
Node of Ranvier
Myelin Sheath
(Schwann cell)
Axon hillock
Nucleus
Nucleolus
Membrane
Microtubule
Nucleus
(Schwann cell)
Mitochondrion
Smooth ER
Microfilament
Microtubule
Axon
Synapse
(Axodendritic)
Dendrites

5. **Brain data**

fMRI, EEG, other

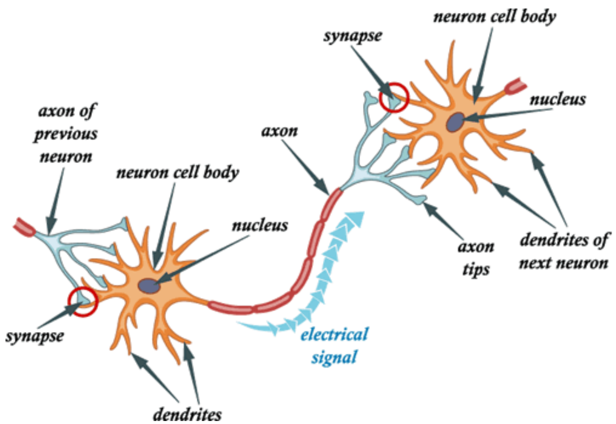
Spatial information

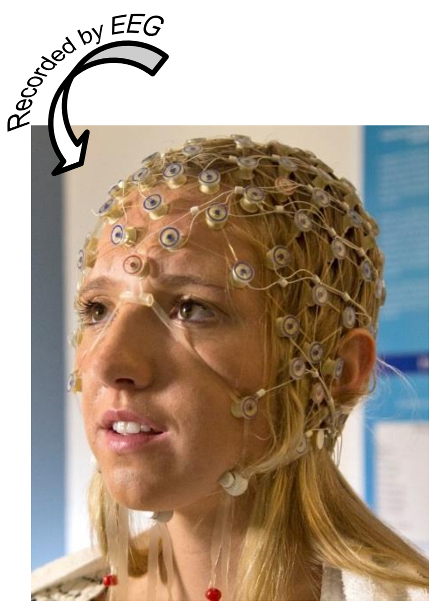




Modelling simultaneously EEG and fMRI data is an open problem:
- different time scales
- different spatial resolution

EEG data measurement and modelling

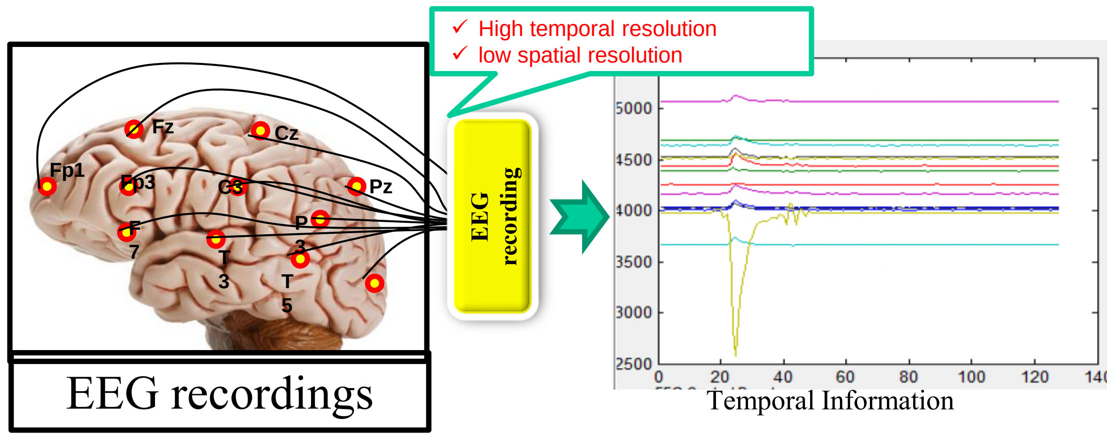




Electroencephalography (EEG) is the recording of electrical activity along the scalp.

EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. Ions of similar charge repel each other, and when many ions are pushed out of many neurons at the same time, volume conduction is generated within neurons.

This electrical signal can be measured by EEG.



Properties:

- ✓ EEG provides high temporal resolution (sampling rates between 250 and 2000 Hz);
- ✓ Unable to provide a precise localisation of the neuron activation;
- ✓ electrodes record sums of activity from cortical sources (unclear spatial resolution);

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Course References

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2. N. Kasabov Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1996 (additional reading)
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17. 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, licence CC BY 4.0,

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- https://www.scopus.com/authid/detail.uri?authorId=35585005300

6. Questions, exercises, assignments and project work

1. Why do we need to learn about how the brain processes information?
2. How is learning organised in the human brain?
3. What data can be measured from the human brain?