PART II. The human brain

Chapter 3

Deep learning and deep knowledge representation in time-space the human brain

Spiking neural networks (SNN) and the deep learning algorithms for them have been inspired by the structure, the organisation and the many aspects of deep learning and deep knowledge representation in the human brain. This chapter presents basic information about brain structures and functions and reveals some inner processes of deep learning and deep knowledge representation.

The chapter has the following sections:

3.1. Time-space in the brain

3.2. Learning and memory

3.3. Neural representation of information

3.4. Perception in the brain is always spatio/specro temporal

3.5. Deep learning and deep knowledge representation in the brain

3.6. Neurons and information transmission between neurons through synapses

3.7. Measuring brain activities as spatio-temporal brain data (STBD)

3.8. Chapter summary and discussions

3.1. Time-space in brain

Interpreting the opening book citation by Vasil Levski, we can say here: T*ime is in our brain and the brain exists in Time.*

The brain (80bln neurons, 100 trillions of connections) has a complex spatial structure which has evolved over 200mln or so years of evolution. It is the ultimate information processing machine. Three, mutually interacting, memory types learned in the brain are:

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

Spatio/spectro temporal evolving processes are manifested at different *time* scales, e.g.:

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

More importantly, the brain learns as a *deep learning* mechanism, creating long neural network connections from external spatio-temporal data and from internal activities. These connections represent *deep knowledge*.

It is estimated that there are 10^{11} - 10^{12} of neurons in the human brain [1]. Three quarters of neurons form a thick cerebral cortex that constitutes a heavily folded brain surface. Cerebral cortex is thought to be a seat of cognitive functions, like perception, imagery, memory, learning, thinking, etc. The cortex cooperates with evolutionary older subcortical nuclei that are located in the middle of the brain, in and around the so-called brain stem (Fig. 1).

Subcortical structures and nuclei are comprised for instance of basal ganglia, thalamus, hypothalamus, limbic system and dozens of other groups of neurons with more or less specific functions in operations of the whole brain. For example, the input from all sensory organs comes to the cortex pre-processed in thalamus. Emotions and memory functions depend upon an intact limbic system. When one of its crucial parts, hippocampus, is lesioned, humans (and animals) loose their ability to store new events and form new memories. When a particular cortical area has been damaged, a particular cognitive deficit follows. However, all the brain parts, either cortical or subcortical, are directly or indirectly heavily interconnected, thus forming a huge recurrent neural network (in the terminology of artificial neural networks). Thus, we cannot speak of totally isolated neuroanatomic modules.

Fig. 1, shows a schematic functional division of the human cerebral cortex and Fig.2 shows both the cortical areas and the inner areas of the human brain. One third of the cortex is devoted to processing of visual information in the primary visual cortex and higher-order visual areas in the parietal cortex and in the infratemporal cortex. Association cortices take about one half of the whole cortical surface. In the parietal-temporal-occipital association cortex, sensory and language information are being associated. Memory and emotional information are associated in the limbic association cortex (internal and bottom portion of hemispheres). The prefrontal association cortex takes care of all associations, evaluation, planning ahead and attention. Language processing takes place within the temporal cortex, parietal-temporal-occipital association cortex, and frontal cortex.

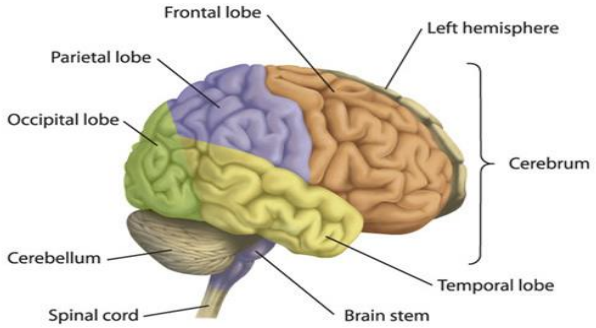

Figure 1. Functional cortical areas of the brain (after [7]).

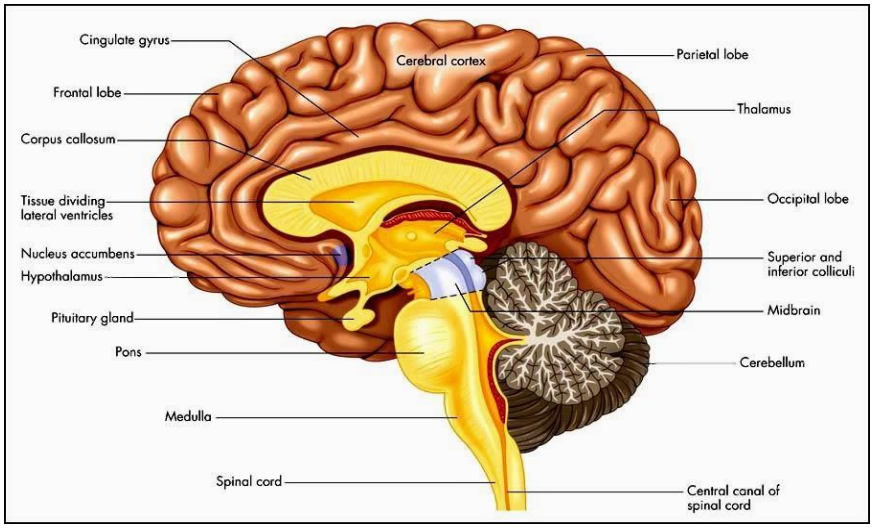

Figure 2. A view of the brain as both cortical and inner areas (after [7, 72]).

At the border between the frontal and parietal lobes, there is a somatic sensory cortex, which processes touch and other somatosensory signals (temperature, pain, etc.) from the body surface and interior. In the front of it, there is a primary motor cortex, which issues signals for voluntary muscle movements including speech. These signals are preceded by the preparation and anticipation of movements that takes place in the premotor cortex. The plan of actions and their consequences, inclusion and exclusion of motor actions into and from the overall goal of an organism, are performed within the prefrontal association cortex. Subcortical basal ganglia participate in preparation and tuning of motor outputs, in the sense of initiation and the extent of movements. Cerebellum executes routine automatized movements like walking, biking, driving, etc. We want to point out that there are far more anatomical and functional subdivisions within each of the mentioned areas.

Functions, or better, dominances of the right and left hemispheres in different cognitive functions are different [1] (Fig. 3). The dominant hemisphere (usually the left one) is specialized for language, logical reasoning, awareness of cognitive processes and awareness of

the results of cognitive processes. Although the non-dominant hemisphere (usually the right one) is able to carry out cognitive tasks, it is not aware of them nor their results. It is specialized for emotional and holistic processing, intra- and extrapersonal representation of space. Its intactness is crucial for the awareness of the body integrity [2]. Lesion of the parietal cortex including the somatosensory cortex leads to the so-called anosognosia. The limbs and the body are intact but the cortical and mental representations become missing. Patients who have undergone a stroke to the right parietal lobe, neglect the left half of their body, in spite they can see it. It is not a consequence of the left hemiparalysis. Mirror damage to the left parietal lobe does not lead to anosognosia. It seems that the right hemisphere is dominant in mental representations of intra- and extrapersonal space. In other words, subjective experience of the body self depends upon specific brain mechanisms, namely an integrity of primary and higher-order somatosensory cortical areas in the right hemisphere [2]. Although, right part of the body is represented in the right somatosensory cortex and the left half of the body in the right hemisphere, the latter seems to have a special role in the integral self-awareness.

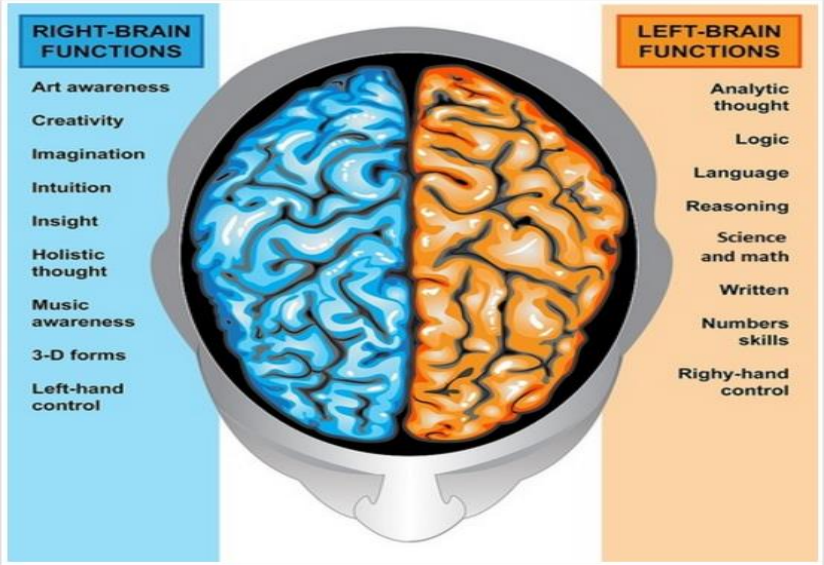

Figure 3. Different part of the brain are allocated to perform different functions (after [72])

Several structural brain atlases have been created to support the study of the brain and to better structure brain data. Probably the first attempt was made by Korbinian Brodmann, who created a cytoarchitectonic map of the human brain, published in 1909. The map presents 43 distinctive areas of the cerebral cortex. Each Brodmann area (BA) is characterized by a distinct type of cells, but it also represents distinct structural area, distinct functional area (e.g. BA17 is the visual cortex), distinct molecular area (e.g. number of neurotransmitter channels) (see Fig. 4).

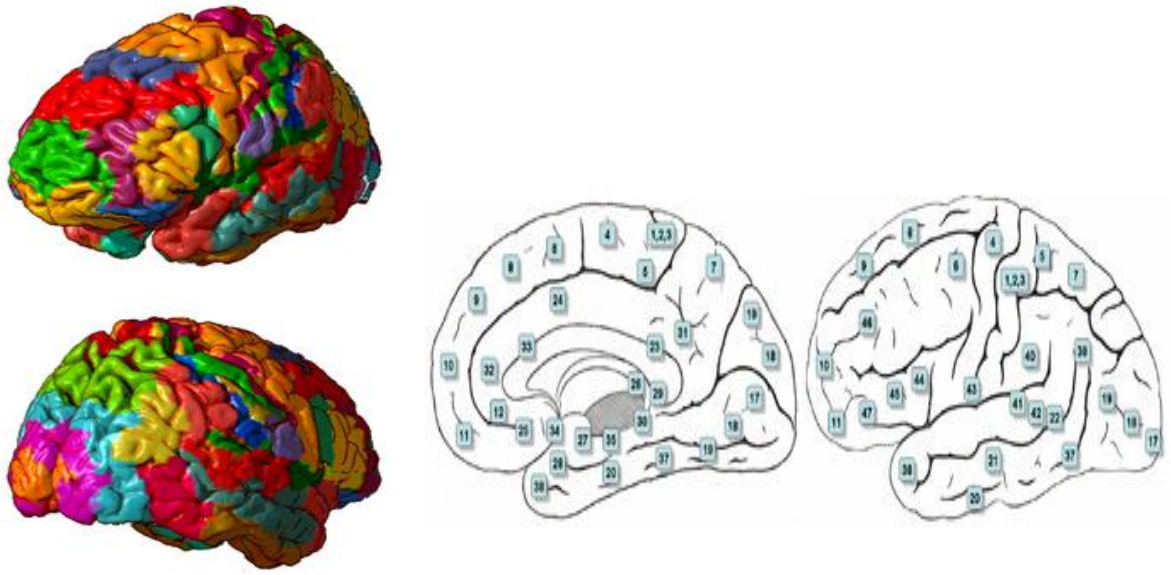

Figure 4. Brodmann areas (after [72])

For many years, the standard 1998 Talairach Atlas brain [3] has served as the casual standard for reporting brain activation locations in the functional and structural brain mapping studies. They have created a co-planar 3D stereotaxic atlas of the human brain that can be used to study it from different subjects and collected using different methods. A software called Talairach Daemon (Fig. 5) is publicly available for download can be used to calculate (x, y, z) Talairach coordinates of any given point on the brain image together with its corresponding Brodmann area. By using this software, brain areas can be labelled accordingly in different visualization colours as depicted in Figure .

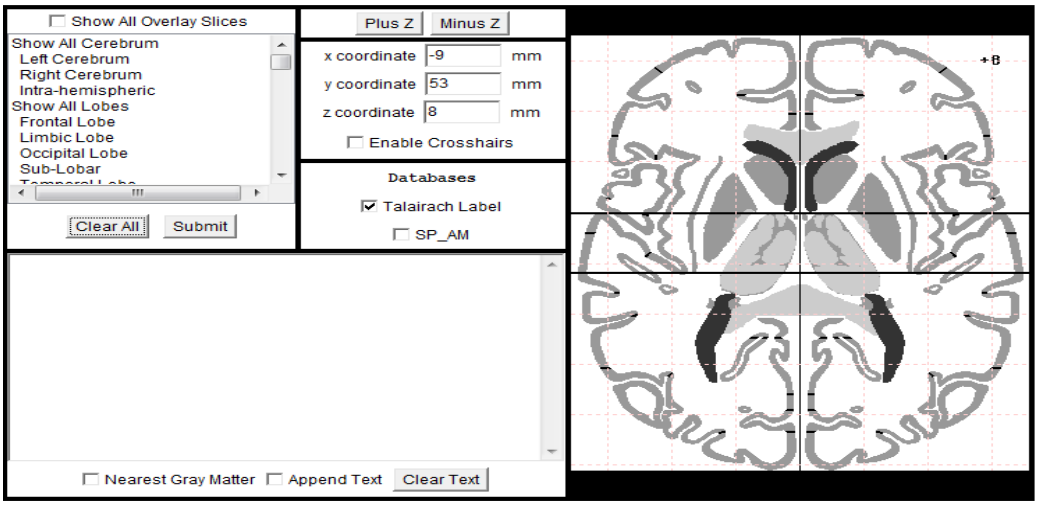

Figure 5. The Talairach Daemon Software for brain areas visualization (http://www.talairach.org/applet/)

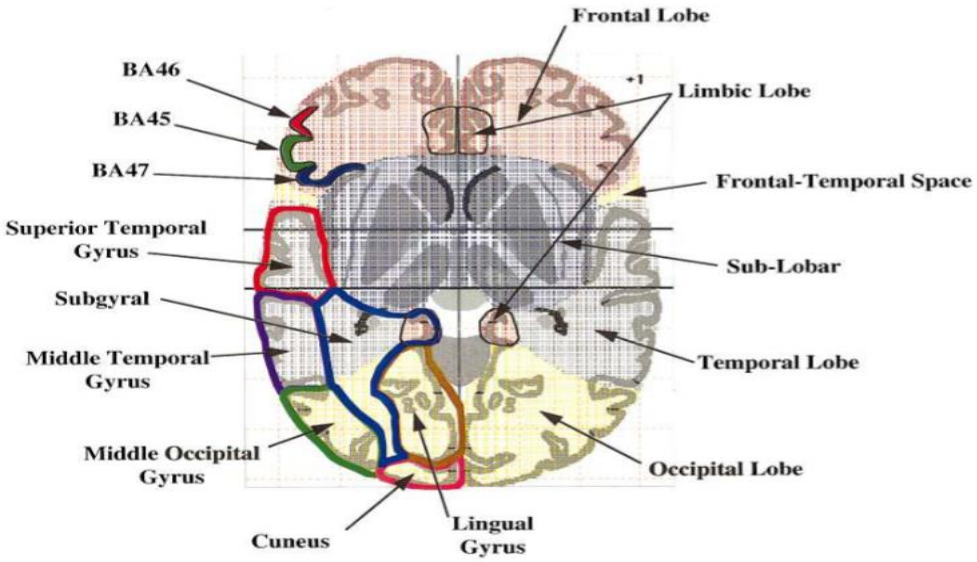

Figure 6. The Talairach atlas with lobe labels (illustrated with patterned colour fills), gyral structures (illustrated with bold colour outlines), and several Brodmann areas (illustrated with solid colour fills) [4].

While Talairach template is derived from the analysis of a single brain, another template which is referred to as Montreal Neurological Institute (MNI) coordinates is derived from the average of MRI data across individuals, for instance MNI152 and MNI1305 [5]. Another well-known brain template is proposed by the International Consortium for Brain Mapping (ICBM) and its few releases include ICBM452, ICBMChinese56, ICBM AD for Alzheimer Disease and ICBM MS for Multiple Sclerosis [6].

3.2 Learning and Memory

Capability of learning and memory formation is one of the most important cognitive functions. Our identity largely depends upon what we have learned and what we can remember. We can divide the study of learning and memory into two levels:

1. The system level (where?) that attempts to answer the question which brain parts and pathways the memory trace is stored in – the top-down approach, which will be the topic of this section, and
2. Molecular level (how?), which is devoted to investigation of the ways of coding and storage of information at the cellular and molecular level – the bottom-up approach, which will be introduced in the next chapter.

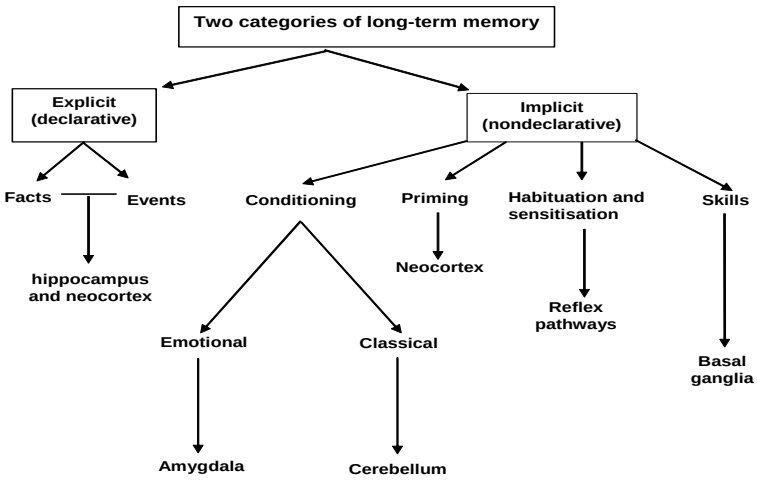

Figure 7. Different kinds of long-term memory fall under two general categories: explicit and implicit (from [7])

It has been long recognized that there is a short-term memory and a long-term memory. Short-term memory lasts for a few minutes and is also called the working memory. It occurs in the prefrontal cortex, although other parts of the cortex relevant to the memory content are activated too [8]. The learning process and the process of long-term memory formation can be divided into these four stages:

1. Encoding. Attention focus and entering of new information into the working memory. Finding associations with already stored memories.
2. Consolidation. The process of stabilization of new information, transformation into a long-term memory by means of rehearsal.
3. Storage. Long-term storing of information in memory.
4. Recall. Retrieval of information into the working memory.

Based on clinical, imaging and animal studies we can divide long-term memory into two main categories that have different subtypes with different mechanisms and different localizations in the brain (Fig. 2). Explicit (declarative) memory is a memory of facts (semantic memory) and a memory of events (episodic memory). Recall from explicit memory requires conscious effort and stored items can be expressed in language. Hippocampus is a crucial but only a transitory stage in the explicit memory. How is the explicit memory formed? Information comes to brain through the sensory organs (visual, auditory, olfactory, tactile), and proceeds through subcortical sensory nuclei and sensory cortical areas into multimodal association areas, like for instance the parieto-temporo-occipital association cortex, limbic association cortex and

the prefrontal association cortex. From there the information is relayed through parahippocampal cortex, perirhinal cortex and entorhinal cortex into the hippocampus. From hippocampus the information is relayed to subiculum from where it returns back to entorhinal cortex and all the way back to association cortical areas. Thus the brain circuit for the long-term explicit memory storage forms a re-entrant closed loop. According to experimental data, the "synaptic re-entry reinforcement" or SRR hypothesis and the corresponding computational model have been formulated and simulated [9, 10]. According to this hypothesis, after initial learning, reactivation of hippocampal memory traces repeatedly drives cortical learning. Thus, a memory trace (engram) is stored after many repetitions. Repeated reinforcement of synapses during the reactivation of memory traces could lead to a situation in which memory traces compete, such that the strengthening of one memory is always at the expense of others, which are either weakened or lost entirely. In other words, a single memory stored in a neural network is either lost (owing to synaptic decay) or strengthened and maintained by repeated rounds of synaptic potentiation each time the memory is reactivated. Once cortical connections are fully consolidated and stabilized, the hippocampus itself becomes dispensable. Differences in the frequency with which memory traces are either consciously or subconsciously recalled could be another factor affecting the selection of which memories are consolidated. An increasing amount of evidence suggests a role of sleep in memory consolidation by means of learning-induced correlations in the spontaneous activity of neurons and replaying the patterns of wake neural activities during sleep [11, 12]. Although others point out that people lacking REM sleep do not show memory deficits and that a major role of sleep in memory consolidation is unproven [13]. An interesting question is how the degradation of out-dated hippocampal memory traces occurs after memory consolidation is finished. The most recent hypothesis is that memory clearance may actually involve new-born neurons. Neurogenesis in the dentate gyrus of the hippocampus persists throughout life in many vertebrates, including humans. The progenitors of these new neurons reside in the subgranular layer of the dentate gyrus [14,15].

The implicit or non-declarative memory serves to store the perceptual and motor skills and conditioned reactions. Recall of stored implicit information occurs without a conscious effort, automatically and the information is not expressed verbally. Basal ganglia and cerebellum are important for acquisition of motor habits and skills that are characterized by precise patterns of movements and fast automatic reactions. Cerebellum is the key structure for conditioning. Conditioned emotional reactions require amygdala in the limbic system. Nonassociative learning like habituation and sensitisation occur in primary sensory and reflex pathways. Priming is an increase in the speed or accuracy of a decision that occurs as a consequence of a

prior exposure to some of the information in the decision context, without any intention or task related motivation, and occurs in neocortex.

Although implicit and explicit learning concern different memory contents, they share cellular and molecular mechanisms [16]. These mechanisms will be one of the topics of the next chapter. Later we also introduce the genetics of learning and memory and the neurogenetic computational model.

3.3. Neural Representation of Information

The first principle of representation of information in the brain is redundancy. Redundancy means that every information (meant in any sense) is stored, transmitted and processed by a redundant number of neurons and synapses so that it does not become lost when neural networks undergo damage, for instance due to aging. When neural networks get damaged, their performance does not drop down to zero abruptly, like in a computer, but instead it degrades gracefully. Computer models of neural networks also confirm the idea that a degradation of performance with the loss of neurons and synapses is not linear but instead neural networks can withstand quite substantial damage, and still perform well. Next, the contemporary view on the nature of neural representation is such that information (in the sense of content or meaning) is represented by place in the cortex (or in general in the brain). However, this placing is a result of anatomical framework and shaping by input, i.e. by experience-dependent plasticity. For instance, a sound pattern for the word “apple” is represented in the auditory areas of the temporal cortex. It is represented as a spatial pattern of active versus inactive neurons. This neural representation is associated (connected) through synaptic weights with the neural representation of a visual image of apple in the parietal cortex, with the neural representation of an apple odor in the olfactory cortex, with memories on the grandma garden and facts about apples, being represented in some other areas of the cortex, etc. Neural representations (that is distributions or patterns of active neurons) within particular areas and their associations between areas appear as a result of learning (i.e. synaptic plasticity). Different objects are represented by means of different patterns or distributions of active neurons within cortical areas. Therefore we speak about the so-called distributed representations.

Current hypothesis states that recall from memory is an active process. Instead of passive processing of all electrical signals that arrive from hierarchically lower processing levels, cortical neural networks should be able to use fragments of activity patterns to fill in the gaps, and thus quickly re-create the whole neural representation. The filling-in process can be nicely modelled by means of model neural networks (Fig. 8). Neural representations (patterns of

activities) are stored in the matrix of synaptic weights through which neurons in the network are interconnected. The weight distribution storing a particular object representation is created due to an experience-dependent synaptic plasticity (learning). When a sufficiently large portion of this neural representation is activated from outside the network, few electric signals along all the synapses in the network quickly switch on the correct remaining neurons in the representation.

Neural representations in the sense of patterns of activity have a holistic character. Patterns of activity are being recalled (restored) as a whole. Thus, we can see a nice relation between the character of neural representations and gestalts. Gestalt psychology was developed at the beginning of the 20th century by Max Wertheimer, Kurt Koffka and Wolfgang Köhle in Germany. Gestalt psychology considers holistic mental gestalts (shapes, forms) to be the basic mental elements. For the gestalt to be stored and recalled, certain rules must be fulfilled, like the rules of proximity, good continuation, symmetry, etc. These rules have been experimentally verified.

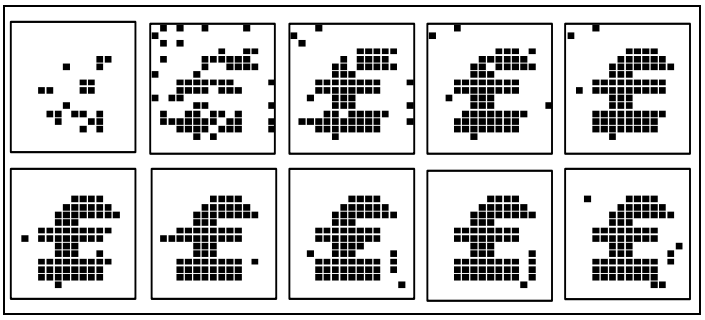

Figure 8. Illustration of spontaneous re-creation of neural representation after few input impulses (figure in the uppermost left corner). Black pixel represents a firing neuron while blank pixel represents a silent neuron. Between each pattern of activity from left to right (1 ms time frame), neurons in the network exchange only one impulse. Thus, basically after exchanging only two-three spikes, the memory pattern is re-created. Network can reverberate the restored memory pattern until a different external input arrives (from [7])

To conclude, neural representations of objects are stored in the matrix of synaptic weights as a whole. We are not able to trace down a sequence of steps leading to the holistic percept. Synaptic weights implicitly bind together parts of the pattern.

3.4 Perception in the brain is always spatio/spectro-temporal

Perception in the brain provides information for learning and development. The five senses of perception (visual auditory, tactile, gustatory and olfactory) send information to the brain as always spatio/spectro-temporal. Even a static picture is perceived in the retina as activity of cells that are activated differently for different colors and intensity of the pixels of the picture, the brighter pixels causing the first spikes to be sent to the visual cortex from the retina. This is also demonstrated in Chapter 9 when a SNN system is trained on fMRI data of a person seeing a picture.

Perception is accompanied by sensory awareness, and therefore we will describe the underlying neural processes in relation to the next section on consciousness. We will concentrate on visual perception and visual awareness since similar principles apply to all sensations. Neurons in different areas of the visual cortex respond to various elementary features, like oriented edges of light intensity (bars), binocular disparity, movement, color, etc. [1]. Visual areas in the occipital, parietal and inferior temporal cortex, though reciprocally connected, are hierarchically organized. Results of processing at lower hierarchical levels are relayed to higher-order areas. Neurons in higher-order areas respond to various combinations of elementary features from lower-order areas. In primates, based on matching psychophysical and physiological data, three main visual systems, relatively independent but mutually heavily interconnected, have been identified: the "magno", "parvo" and the color system [17]. The "magno" system is responsible for perception of movement, depth and space, and separation of objects. Several cues leading to the depth perception have been identified: stereopsy, depth from perspective, depth from mutual movement and occlusion, etc. The "parvo" system is responsible for shape recognition. For separation and recognition of objects, we use separation based on movement, separation from background, filling in of borders, shape from shading, etc. The color system is responsible for color perception. With respect to cortical neurons belonging to these three systems, they possess different combinations and ranges of these four physiological properties: sensitivity to color (small/ large), sensitivity to the light contrast (small/large), temporal resolution (small/large), spatial resolution (small/large). These are the so-called elementary features of visual objects. Elementary features belonging to one visual object activate different and spatially separated groups of neurons within the cerebral cortex.
Binding of spatially separated neurons coding for features belonging to one visual object could be performed by transient synchronization of firing of these neurons [18-20]. Similar synchronous oscillations of neurons were detected also in auditory, somatosensory, parietal, motor, and prefrontal cortices in the case of auditory, tactile and other perceptions, respectively

[21]. Oscillations of neurons with frequencies around and above 40 Hz (long known as gamma oscillations) have been detected in the cerebral cortex of humans, primates and other investigated mammals, in particular as a result of sensory stimulation. This synchronization occurs over relatively long distances (mm to cm), between different cortical areas, between cortex and thalamus, between the two hemispheres.

Synchronization means that neurons discharge with the same frequency and the same phase. This results in a distributed pattern of simultaneously firing neurons. Neural correlates of different objects can differ in (a) which neurons are members of the pattern, (b) which is the particular frequency of their synchronization, and (c) which is the phase of their synchronization. Thus, transient synchronous gamma oscillations have been suggested as a possible candidate for the mechanism of binding many elementary features belonging to one object to one transient whole corresponding to a percept. Establishment of transient synchrony is based upon the underlying synaptic connectivity.

An experimental phenomenon strongly suggesting a one-to-one correspondence between transient synchronizations and perception is binocular rivalry. During binocular rivalry, each eye is constantly stimulated with a different pattern. Visual percept is neither an average of these two patterns nor their sum. Instead, a random alternation between the two percepts occurs as if they were competing with each other, hence the term binocular rivalry [22], discovered that neurons which respond to one or the other pattern are synchronized only during the corresponding percept. Thus, although the pattern is constantly stimulating an eye, cortical neurons get synchronized only when the pattern is perceived.

An important study of Rodriguez et al. in [23] has demonstrated that perception of faces in humans is accompanied by a transient (~180 ms) synchronization of gamma activity in hierarchically highest visual areas in the parietal cortex and premotor areas in the frontal cortex (Fig.9). Thus, transient synchronizations may accompany also other cognitive processes not only perception. W. Miltner et al. [24] indeed detected synchronization of gamma oscillations during an associative learning. Humans were supposed to learn to associate a visual stimulus with the tactile stimulus. A selective synchronization occurred between the visual cortex and that part of somatosensory cortex which represented the stimulated hand, during and after the learning. When people forgot the learned association, synchronization between these two stimuli, or rather between neural responses to these two stimuli, disappeared.

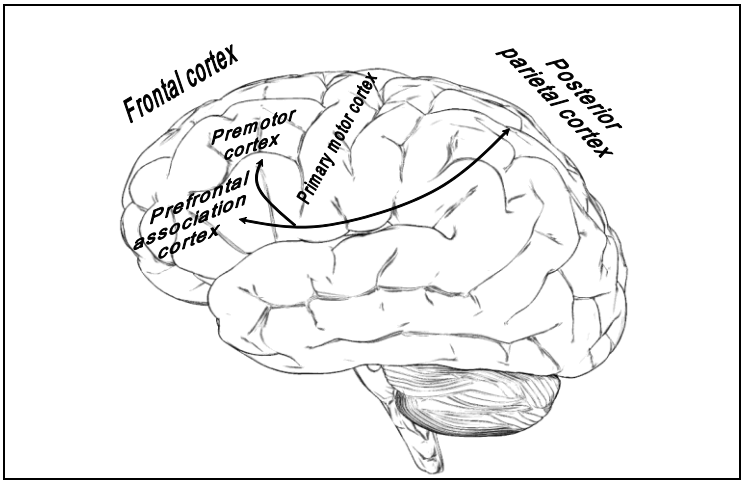

Figure 9. Corticocortical connections between the posterior parietal cortex and the main subdivisions of the frontal cortex. Illustrated areas showed increased coherence within the 40 Hz band in the Rodriguez et al.'s experiment on recognition of Mooney faces. When a human face was recognized, transient coherence occurred in the time window of 180×360 ms after the beginning of the picture presentation (from [7]).

Currently, transient (100–200 ms) synchronous gamma oscillations are being studied as a promising candidate for the mechanism of binding many elementary features belonging to one object to one transient whole corresponding to a percept of that object [25, 26]. Such synchronized activity summates more effectively than nonsynchronized activity in the target cells at subsequent processing stages, and the activity can spread to a longer distances. If so, synchronization could increase the effect that a selected population of neurons has on other populations with great temporal specificity (in the range of milliseconds). There is also evidence that synchrony is important for inducing changes in synaptic efficacies and hence facilitate transfer of information into memory. Different objects in one scene may be associated with different phase-locked synchronous oscillations within the gamma frequency band. Thus, increased coherence between brain areas confined to a narrow band around 40 Hz may denote a holistic perception of a complex stimulus. Based on experimental findings, crucial neural conditions for a conscious percept to be experienced is [19, 27-30]:

- Over the chain of higher-order sensory areas with the areas that have direct connections to the frontal cortex being at the end of this chain (e.g. the posterior parietal cortex), and over the evolutionary youngest cortical areas, i.e. the frontal and prefrontal cortex, certain suprathreshold quantity (number) of neurons must be coherently active for a certain time of 100×200 milliseconds.

Generating sensory awareness involves the process of attention. Several areas in the prefrontal cortex are crucially involved in attention, namely areas 8Av (major connections with the visual

system), 8Ad (major connections with the auditory system) and 8B (major connections with the limbic system) [8]. Attentional selection may depend on appropriate binding (coherence) of neuronal discharges in sensory areas in two simultaneously active directions: an attentional mechanism in prefrontal cortex could induce synchronous oscillations in selected neuronal populations (top-down interaction), and strongly synchronized cell assemblies could engage attentional areas into coherence (bottom-up interaction) [19].

Another prefrontal areas activated during sensory perception include Brodmann areas 9, 10, 45, 46, 47 (see Fig. 10). These prefrontal areas are known to be involved in an extended action planning. In addition, these prefrontal areas plus the posterior parietal cortex are known to be involved in the working memory. Posterior parietal cortex is also known to be involved in mental imagery. For planning of actions it is necessary to keep track of at least one sequence of partial actions, hence the overlap between planning and memory mechanisms. It might be that sensory contents reach awareness only if they are bound to prefrontal areas via the posterior parietal cortex and thus have a possibility to become part of the working memory and action planning [25]. In turn, action planning may influence organization of attentional mechanisms and thus what is being perceived. Actually, the underlying action planning can occur at a subconscious level [31, 32].

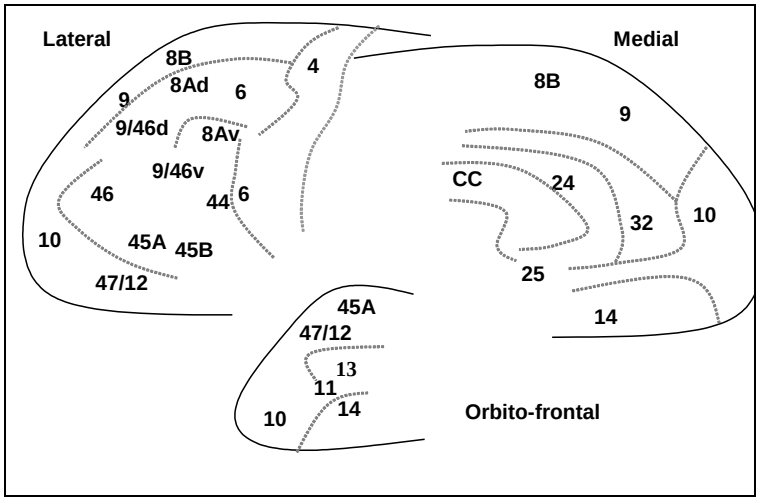

Figure 10. Human prefrontal cortex. Lateral view (from outside), medial view (from inside) and the orbito-frontal view (from below) at the left hemispehere. The same divisions hold also for the right hemisphere. Numbers denote the corresponding Brodmann's areas. CC means Corpus Callosum.

Coherences in the involved areas are generated internally within the cortex and although they are phase-locked, they are not stimulus locked. They are superimposed upon global thalamocortical gamma oscillations which are generated and maintained during cognitive tasks [33]. Thalamocortical oscillations may provide the basic oscillatory modulation of cortical

oscillations. Other cortical mechanisms are then responsible for a precise phase-locking of internal cortical synchronous oscillations. In particular, these are lateral inhibitory and excitatory interactions, regularly bursting layer V pyramidal cells, and spike-timing dependent rapid synaptic plasticity. In the latest, synapses and thus the inputs which do not drive the postsynaptic cell in synchrony are temporary weakened [34].

In [34], this is called ever changing semiglobal coherent activity, the *dynamic core*. The dynamic core corresponds to a large (semiglobal) continuous cluster of neuronal groups that are coherently active on a time scale of hundreds of milliseconds. Its participating neuronal groups are much more strongly interactive among themselves than with the rest of the brain. The dynamic core must also have an extremely high complexity as opposed to for instance convulsions. Each roughly 150 ms, a pattern of semiglobal activity must be selected within less than a second out of a very large, almost infinite, repertoire of options. Thus, the dynamic core changes in composition over time. As suggested by imaging, exact composition of the core varies significantly not only over time within one individual, but also vary significantly across individuals.

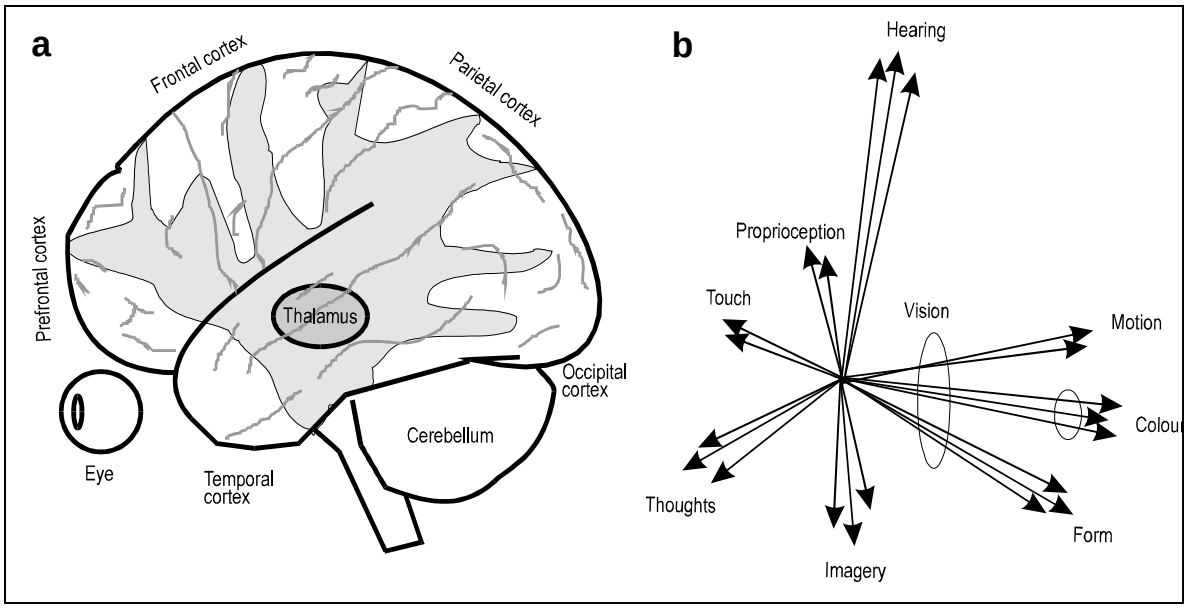

Figure 11. a) Illustration of the dynamic core, a changing coherent semiglobal activity of the brain, which is supposed to be a neural correlate of consciousness. One configuration of the core lasts for about 150 ms. b) Interpretation of the dynamic core as an *N*-dimensional neuronal reference space, where each axis (dimension) denotes some group of neurons which encodes (represents) a given aspect of the conscious experience. Each axis can be broken down into more elementary axes. There can be hundreds of thousands of dimensions (from [7]).

According to [34], the dynamic core consists of a large number of distributed groups of neurons which enter the core temporarily based on their mutual coherence. Connecting groups of neurons into temporarily synchronized whole requires dense recurrent connections between brain areas, along which a reiterated re-entry of signals occurs. Neural reference space for any

conscious state may be viewed as an abstract *N*-dimensional space, where each axis (dimension) stands for some participating group of neurons that code for (represent) a given aspect of the conscious experience. There can be hundreds of thousands of dimensions. The distance from the beginning of the axis represents the salience of that aspect. It may, for instance, correspond to the number of firing neurons within a given group. We would like to point out the interesting similarity between this abstract *N*-dimensional neural space and the conceptual spaces introduced by [35].

What would be, in this theory, a neural basis for subconsciousness? The same group of neurons may at times be part of the dynamic core and underlie conscious experience, while at other times it may not be part of it and thus be involved in subconscious processing. In [27], have proposed that those active neurons which are not at the moment taking part in the semiglobal activity keep processing their inputs, and results of this processing may still affect behaviour.

We would like to mention also the explanation of neural correlate of qualia or the hard problem of consciousness, according to [34]. Qualia are specific qualities of subjective experiences, like redness, blueness, warmth, pain, and so on. According to the dynamic core hypothesis, pure redness would be represented by one particular state of the dynamic core that is by one and only one point in the *N*-dimensional neural space. This core state would certainly include large participation of neurons that code for the red colour and a small participation of neurons that code for other colours and for anything else. Coordinates of a point in the *N*-dimensional reference neural space are determined by activities of all neuronal groups that are at the moment part of the core. And these activities vary in time and across individuals. Thus, the subjective experience of redness will be different in different people and can be different for the same individual for instance in the morning and in the evening.

Sleep research has revealed that during sleep, humans normally go through two-three cycles of two sleep phases. One of these two phases is the so called REM sleep, according to the accompanying Rapid Eye Movements. EEG activity of the brain during the REM phase is very similar to the EEG activity of the awake brain during cognitive activity. Hence the term paradoxical sleep for the REM sleep phase, as it was not sleep at all. We dream mostly during REM sleep phases. When awakened during the REM phase, we can recall the content of a dream. We experience self-awareness when we dream but not when we are in the deep sleep [36]. Thus "I" is preserved during dreaming as well as the awake-like EEG activity of the brain. When awakened around at the end of the REM phase, we can remember that we dreamt, not knowing about what. When awakened during the non-REM sleep phase, we mostly deny any experience of dreaming. The non-REM sleep phase is also called the deep sleep, and the brain

activity occurs in typical slow large regular waves. Recently, experiment with the spread of activity within neocortex during sleep have revealed that different cortical areas stop communicating over distance with each other during the non-REM sleep – a stage of sleep for which people mostly report no or very little conscious experience on waking [37]. Thus, it seems that the coherent semiglobal activity is disrupted during the non-REM sleep, and so is the conscious awareness.

3.5. Deep learning and deep knowledge representation in time-space the brain

The brain is a complex integrated spatio-temporal information processing machine. An animal or a human brain has a range of structural and functional areas that are spatially distributed in a constrained 3D space. When the brain processes information, either triggered by external stimuli, or by inner processes, such as visual-, auditory-, somatosensory-, olfactory-, control-, emotional-, environmental-, social, or all of these stimuli together, complex spatio- temporal pathways are activated and patterns are formed across the whole brain. For example, '…the language task involves transfer of stimulus information from the inner ear through the auditory nucleus in the 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)…' [38]. Many other studies of spatio-temporal pathways in the brain have been conducted, e.g. birdsong learning [39].

In principle, different 'levels' of spatio-temporal information processing can be observed in the brain, [37], all 'levels' acting in a concert. Spatio-temporal brain data (STBD) related to each of these 'levels' can be collected, but how do we integrate this information in a machine learning model?

Let us trace the visual brain processing in this experiment (see Fig. 12). Projected image stimulates retina for 20 ms. In about 80 ms, neurons in the thalamic LGN (lateral geniculate nucleus) respond. Thalamic neurons activate neurons in the primary visual cortex (V1). Then, activation proceeds to and through higher-order visual areas, V2, V4 and IT. We speak about the so-called "WHAT" visual system, which is assumed to be responsible mainly for classification and recognition of objects. In the highest-order area of this system, i.e. the infratemporal (IT) cortex, activity appears after 150 ms since the picture onset (on average). It is thought that here, in the IT area, the classification process is completed [44]. If we divide 150 ms since the picture onset by the number of processing areas (i.e. retina, thalamus, V1, V2,

V4), on average each of them has only 30 ms for processing of signals. The frontal areas, PFC, PMC and MC, are responsible for preparation and execution of motor response, for what they need only 100 ms. Divided by three, again we get about 30 ms for each area. Since each of the mentioned areas has further subtle subdivisions, each sub area can have only 10 ms to process signals and send them higher in the hierarchy of processing. At the same time, neurons in each area send signals up and down in the stream of hierarchical processing. Whether 10 or 30 ms, it is an extremely short time for processing in one single area. Cortical neurons, when naturally stimulated fire with frequencies of the order of 10 to 100 Hz. A neuron firing with an average frequency of 10 Hz (i.e., 10 impulses in 1000 ms), may fire the first spike in 100 ms from the beginning of stimulation. Thus, during the first 10□30 ms there will be no spikes from this neuron. Another neuron firing with the frequency of 100 Hz fires 1×3 spikes during the first 10×30 ms. In each of the above-mentioned areas, there are millions perhaps milliards of neurons, then these neurons exchange only 1-3 spikes, and the result of this processing is sent higher to higher-order areas, and lower to the lower-order areas. Each neuron receives signals from 10 000 other neurons and sends off signals to the next 10 000 neurons. Synaptic transmission delay in one synapse is about 1 ms. A neuron cannot wait 10 000 ms to receive signals from all its presynaptic neurons. Thus, the signals ought to come almost simultaneously, and not one after another.

Another complication in the neuronal processing of inputs is the fact that firing is a stochastic process. A good model for it is a Poisson stochastic process where the value of dispersion is equal to the value of the mean, thus the dispersion is large. Speaking about firing frequencies of 10 or 100 Hz, we mean average frequencies over relatively long time periods, let us say 500 ms (half of a second). Thus, a neuron firing with the average frequency of 100 Hz does not have to fire a single spike during the first 10-30 ms from the beginning of stimulation, and a neuron firing with the average frequency of 10 Hz may fire four spikes. Thus, to summarize, it is really a problem how neurons code information. So far, this problem has not been solved. In the following section we will introduce several current hypotheses.

Despite the very complex information processing in the brain, we can represent at abstract level the deep knowledge of classifying an image stimulus as a sequence of events (Ei), each of them consisting of a function Fi, that is activated as a location Si at a time Ti, and all of them connected as a piece of deep knowledge (as per the definitions of deep knowledge in Chapter 1).

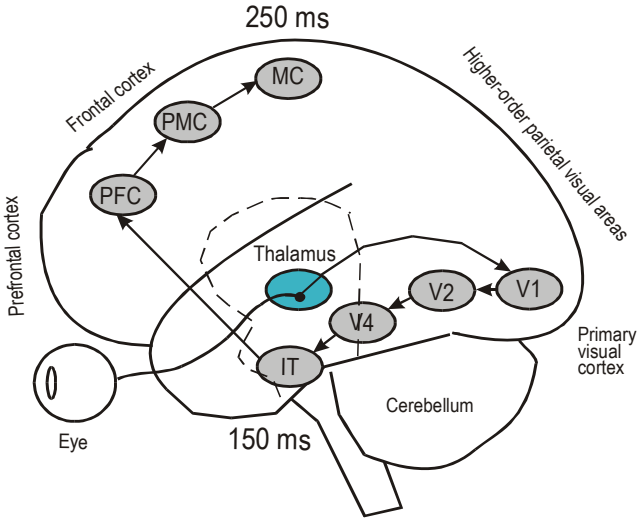

Figure 12. Deep serial processing of visual stimuli in humans for image classification. Location of cortical areas: V1 = primary visual cortex, V2 = secondary visual cortex, V4 = quartiary visual cortex, IT = inferotemporal cortex, PFC = prefrontal cortex, PMC = premotor cortex, MC = motor cortex. The brain has learned through *deep learning* how to process visual stimuli, forming a *deep knowledge*, represented as connections between different spatially located parts of the brain, activated at different times (from [7]). We can represent the deep knowledge of classifying an image stimulus as a sequence of events (Ei), each of them consisting of a function Fi, that is activated as a location Si at a time Ti, and all of them connected as a piece of deep knowledge

Language processing during a simple task of repeating the word that has been heard is the Wernicke-Geschwind model [42] that is a deep and serial activation of brain araeas as a a result of deep learning beforehand. A language task involves many steps of processing as shown in Box 1 and Fig.13, learned as deep learning and representing deep knowledge. The task involves different procedures (named as events Ei in Chapter 1), each event Ei consisting of a function Fi, spatial location Si and time of execution Ti, and all connected in a deep knowledge.

Box 1. Deep knowledge learned and represented in time-space for a language task.

---

1. Event E1: Transfer of information from the inner ear through the auditory nucleus in thalamus to the primary auditory cortex (Brodmann's area 41) (location S1) at time T1.
2. Event E2: Then to the higher-order auditory cortex (area 42) (location S2) at time T2;
3. Event 3: Then it is relayed to the angular gyrus (area 39) (location S3) at time T3. Angular gyrus is a specific region of the parietal-temporal-occipital association cortex, which is

thought to be concerned with the association of incoming auditory, visual and tactile information.

4. Event 4: From here, the information is projected to Wernicke's area (area 22) (location S4) at time T4.
5. Event 5: 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 (location S5) at time T5.
6. Event 6: 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 (location S6) at time T6.

Note: Times Ti and locations Si of events Ei can take either exact values or fuzzy values (e.g. around).

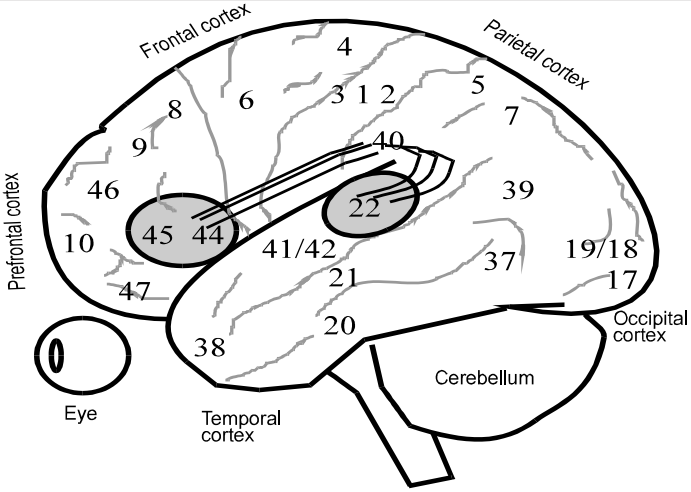

Fig. 13. Deep serial processing in the brain when dealing with words and language (from [7]) Similar pathway is involved in naming an object that has been visually recognized. This time, the input proceeds form retina and LGN (lateral geniculate nucleus) to the primary visual cortex, then to area 18, before it arrives to the angular gyrus, from where it is relayed by a particular component of arcuate fasciculus directly to Broca's area, bypassing Wernicke's area. The brain has learned through *deep learning* how to process visual stimuli, forming a *deep knowledge*, represented as connections between different spatially located parts of the brain, activated at different times (from [7])

The deep learning in the brain is achieved through creating connections between neurons in space and time. The patterns that are formed by these connection represent deep knowledge and enable people to perform different tasks.

3.6. Information and signal processing in neurons and in the brain

3.6.1 Information coding

The brain consists of bullions of neurons and trillions of connections, and each neuron is a complex infortion processing machine, receiving thousands of signals from dendrites that receive signals from other neurons through synaptic connections. The neuron has just one output that emits spikes at certain times when the membrane of this neurons reaches a threshold (Fig.14).

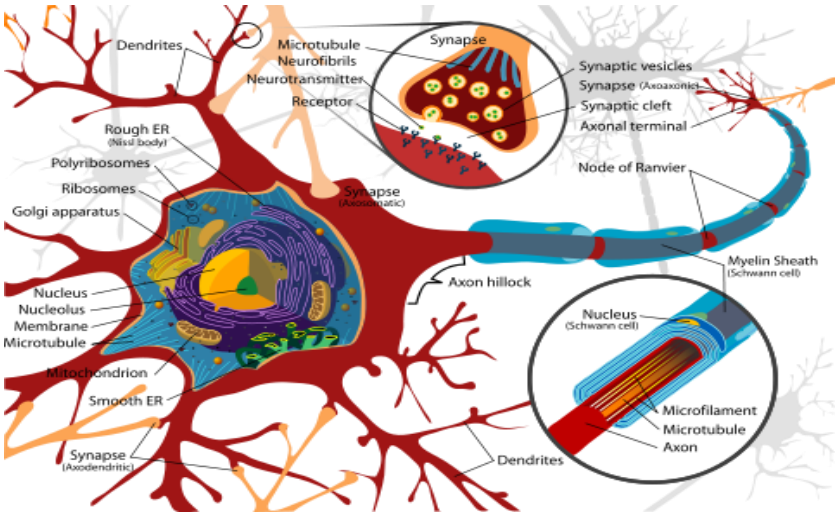

Figure.14. A single neuron is a complex information processing machine (after [72])

Information in the brain is represented and transferred as electrical potentials (spikes) under different encoding mechanisms as discussed below.

Coding Based on Spike Timing

1. *Reverse correlation*. The first option is that the information about the salience of the object feature is encoded in the exact temporal structure of the output spike train. Let us say that two neurons fire three spikes within 30 ms. The first neuron fires a spike train with this temporal structure | || and the second neuron with this temporal structure ||| . By means of the techniques of reverse correlation, it is possible to calculate which stimulus exclusively causes which temporal pattern of which neuron. The main proponents of this theory are Bialek and his co-workers who have made its successful verification in the fly visual system [43].

2. *Time to the first spike*. Let at time instant t_0 a stimulus arrives to the neural network. Neurons that fire the first (let us say in a window of 10 ms) carry the information about the stimulus features. The rest of neurons and the rest of impulses are ignored. This theory is favored by S. Thorpe ([41,44]).
3. *Phase coding*. Information about the presence of the feature is encoded in the phase of neuron's impulses with respect to the reference background oscillation. Either they are in a phase lead or in a phase lag. The information can also depend on the magnitude of this phase lead (lag). This coding is preferred by people investigating hippocampus [45].
4. *Synchronization*. Populations of neurons that represent features belonging to one object can be bound together by synchronous firing. Such synchronization was discovered in the laboratory of W. Singer in the cat visual cortex to accompany percepts [22]. It was also detected in the human cortex during perception of meaningful stimuli (faces) [23].

Rate Coding

1. *Temporal average rate*. In this respect, works of an English physiologist Adrian from the 30-ties of the 20th century are being cited. Adrian found out that the average frequency of a neuron in the somatosensory cortex is directly proportional to the pressure applied to its touch receptor. Similar dependencies have been discovered in the auditory and visual cortices. That is, in the auditory cortex, the heard frequency is encoded by the average firing frequency of auditory neurons, and in the visual cortex, the average frequency of neurons encodes for the salience of its visual elementary feature. This coding is still being considered for stationary stimuli that last up to around 500 ms or longer, so that neurons have enough time to count (integrate) impulses over long time. Neurons that have the highest frequency signalize the presence of the relevant feature.
2. *Rate as a population average*. An average frequency is not calculated as a temporal average but rather as a population average. One feature is represented by a population of many (10 000) neurons, for instance in one cortical column. Upon presence of a feature, most of them are activated. When we calculate the number of spikes in a 10 ms window of all these neurons and divide this number by the number of neurons, we will get approximately the same average frequency as when calculating a temporal average rate of any of these neurons (provided they all fire with the same average rate). This idea has been thoroughly investigated by Shadlen and Newsome [46]. They showed on concrete examples, that by means of population averaging we can get a reliable calculation of neuron's average rates even in the case when they have a Poisson-like distribution of output spikes. Populations that relay the highest number of spikes signalize the presence of the relevant feature.

At present, it is widely accepted that learning is accompanied by changes of synaptic weights in cortical neural networks [1]. Changes of synaptic weights are also called *synaptic plasticity*. In 1949, the Canadian psychologist Donald Hebb formulated a universal rule for these changes: "When an axon of cell A excites cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells so that A´ s efficiency as one of the cells firing B is increased", which has been verified in many experiments and its mechanisms elucidated [47].

3.6.2. Molecular basis of information processing

In cerebral cortex and in hippocampus of humans and animals, learning takes place in excitatory synapses formed upon dendritic spines that use glutamate as their neurotransmitter. In the regime of learning, glutamate acts on specific postsynaptic receptors, the so-called NMDA receptors (*N*-methyl-D-aspartate). NMDA receptors are associated with ion channels for sodium and calcium (see Fig. 15). The influx of these ions into spines is proportional to the frequency of incoming presynaptic spikes. Calcium acts as a second messenger thus triggering a cascade of biochemical reactions which lead either to the long-term potentiation of synaptic weights (LTP) or to the long-term depression (weakening) of synaptic weights (LTD). In experimental animals, it has been recorded that these changes in synaptic weights can last for hours, days, even weeks and months, up to a year. Induction of such long-term synaptic changes involves transient changes in gene expression [48,49].

A subcellular switch between LTD and LTP is the concentration of calcium within spines [50]. We speak about an LTD/LTP threshold. In turn, the intra-spine calcium concentration depends upon the intensity of synaptic stimulation that is upon the frequency of presynaptic spikes. That is, more presynaptic spikes means more glutamate within synaptic cleft. Release of glutamate must coincide with a sufficient depolarization of the postsynaptic membrane to remove the magnesium block of the NMDA receptor. The greater the depolarization, the more ions of calcium enter the spine. Postsynaptic depolarization is primarily achieved via AMPA (amino-methylisoxasole-propionic acid) receptors, however, recently a significant role of backpropagating postsynaptic spikes has been pointed out [51]. Calcium concentrations below or above the LTD/LTP threshold, switch on different enzymatic pathways that lead either to LTD or LTP, respectively. However, the current value of the LTD/LTP threshold (i.e. the

properties of these two enzymatic pathways) can be influenced by levels of other neurotransmitters, an average previous activity of a neuron, and possibly other biochemical factors as well. This phenomenon is called metaplasticity, a plasticity of synaptic plasticity [52]. Dependence of the LTD/LTP threshold upon different postsynaptic factors is the subject of the Bienenstock, Cooper and Munro (BCM) theory of synaptic plasticity [53] (for a nice overview see for instance [54]). The BCM theory of synaptic plasticity has been successfully applied in computer simulations to explain experience-dependent changes in the normal and ultrastructrally altered brain cortex of experimental animals [55,56].

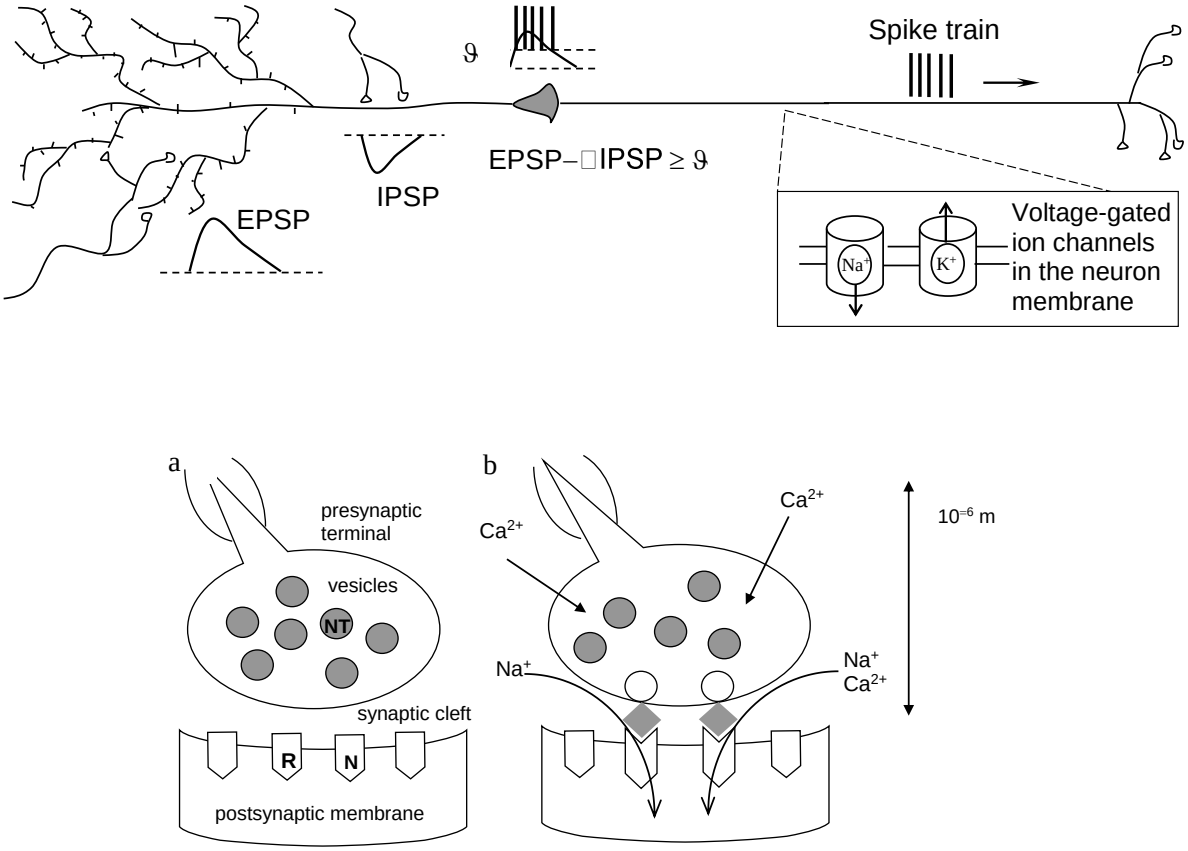

Figure 15. Scheme of synaptic transmission. a) A synapse is ready to transmit a signal. b) Transmission of electric signal (a spike) in a chemical synapse upon arrival of action potential into the terminal. NT = neurotransmitter, R = AMPA-receptor-gated ion channel for sodium, N = NMDA-receptor-gated ion channel for sodium and calcium (from [7]).

Dendrites of cortical excitatory pyramidal neurons are abundant in tiny membrane extensions called spines. They are named so because they resemble in shape the spines on the rose stem. About 80% of all synaptic connections in the cerebral cortex are excitatory and vast majority of them is formed on the heads of synaptic spines. For many years the role of spines was a

mystery. Nowadays it is accepted that they play several important roles in synaptic plasticity and learning.

First, it was discovered that spines change their size, shapes and numbers during the induction and maintenance of LTP [57,58]. There are growth changes on spines, like spine head swelling, spine neck thickening, and increase in appearance of spines with mushroom-shaped heads. Morphological properties of spines and changes in their shape were first supposed to play a role in affecting the efficacy of synaptic transmission by means of changes in the input resistance [59]. Long, thin spines create a big input electrical resistance, while short, stubby spines create a smaller input resistance. Later, a role in sequestering and amplifying the calcium concentrations was suggested to be the main role of spines [60]. Through this role a mechanisms for saturation and stopping the infinite growth of synaptic weights was proposed, as well as the role in the LTP/LTD threshold [61]. While all these effects can take place, another important role for spines was suggested in the transport of new receptors into the spine head [62]. This model is based on our older hypothesis that the changes in efficacy of excitatory dendritic spine synapses can result from the fusion of transport vesicles carrying new membrane material with the postsynaptic membrane of spines [63]. Spacek and Harris indeed found structural evidence for exocytotic activity within spines in hippocampal CA1 pyramidal neurons [64]. Smooth vesicles of the diameter around 50 nm occurred in the cytoplasm of spine heads, adjacent to the spine plasma membrane, and fusing with the plasma membrane. In addition, Lledo et al. showed that inhibitors of membrane fusion blocked or strongly reduced LTP when introduced into CA1 pyramidal cells [65]. On the other hand, an increase in synaptic strength was elicited when membrane fusion was facilitated. In the CA1 region, LTP requires the activation of the NMDA glutamate receptors and a subsequent rise in postsynaptic calcium concentration. Besides other roles, Ca^{2+} plays a crucial role in the final stage of vesicle fusion with the membrane, and the number of fused vesicles is proportional to $[Ca^{2+}]$ [66]. Since LTP in CA1 neurons is accompanied by appearance of AMPA subclass of glutamate receptors [67], it is reasonable to assume that vesicles can be a mean of their insertion. Indeed, Kharazia et al. [68] observed GluR1 (a subunit of AMPA receptors) containing vesicles associated with the cytoplasmic side of some GluR1-containing cortical synapses. Moreover, tetanic stimulation induces a rapid delivery of GluR1 into spines and this delivery requires activation of NMDA receptors [69].

Another effect of the vesicle fusion with the spine membrane would be the shaping and growth of the spine, which were observed during the induction and maintenance of LTP. However, prior to fusion the vesicles must get very close to the plasma membrane. The main mechanism for displacement of vesicles within axons and dendrites is the fast active transport

with the speeds of 0.001- 0.004 m/ms [70]. Fast transport depends on the direct interaction of transported vesicles with microtubules via the translocator kinesin-like molecules [70]. However, microtubules do not enter spines [64]. Thus, while the fast transport can bring vesicles close to the walls of dendritic shafts, another mechanism must come into play within spines themselves. The first natural candidate for this mechanism can be the diffusion of vesicles. However, we have shown that an electrophoretically driven, directed motion of negatively charged vesicles towards the spine head, evoked by the synapse stimulation itself can be ten times faster [62].

At a molecular level, different genes, that affect the activity of neuro-receptors and neuro-trasmitters, such as GABA, AMPA, NMDA are expressed differently in different parts of the brain that defines the functioning of these parts. An example is shown in Fig. 16. Information, related to the expression of genes in the brain can be used for neurogenetic modelling as discussed in another chapter of the book.

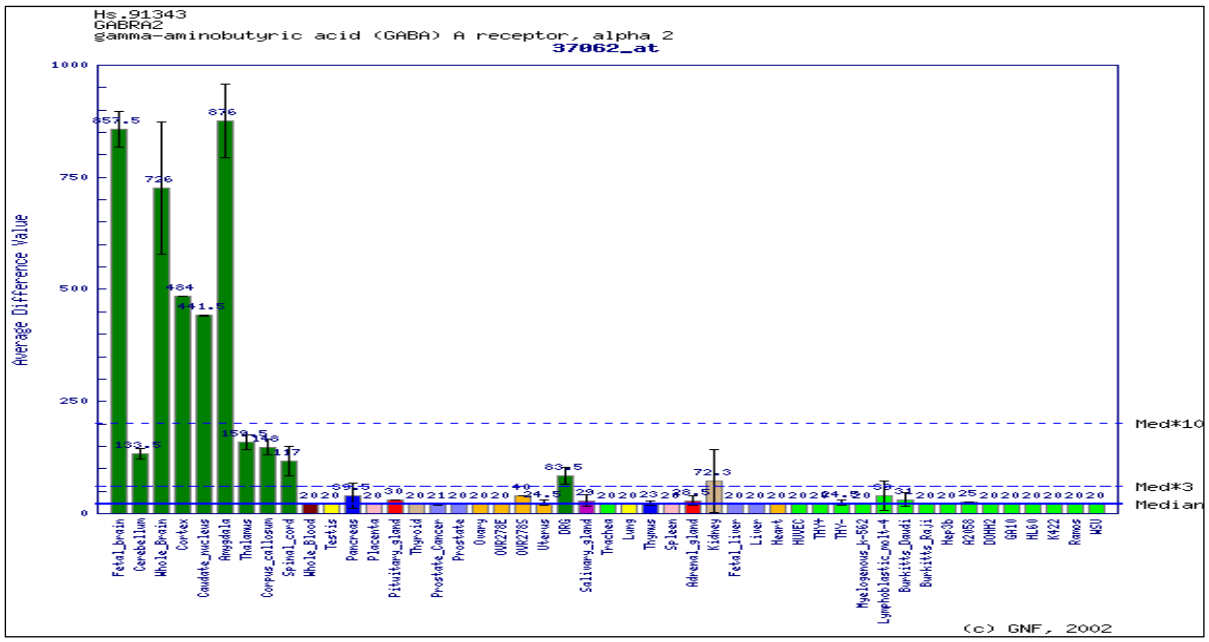

Fig.16. The expression of the GABRA2 gene causes the production of the GABA receptor in the synapses of neurons, and it is differently expressed in different spatially located parts of the brain (from Gene Expression Atlas, http://expression.gnf.org/cgi-bin/index.cgi)

3.7. Measuring brain activities as spatio/spectro-temporal data

3.7.1. General notions

At present, a number of techniques is available to investigate where in the brain particular cognitive and other kinds of functions are based. In general, these methods are divided as being invasive or noninvasive. In medicine the term invasive relates to a technique in which the body is entered by puncture, incision or other intrusion. Noninvasive means the opposite that is the technique that does not intrude into the body.

An invasive method of the brain study is the direct *stimulation*. Researchers perform electrical, magnetic or chemical stimulation of some neural circuit or part of it, and observe the consequences. Electrical stimulation is delivered through microelectrodes inserted into the brain. This type of research is done routinely on animals. It can be done on human subjects during the brain surgery when the skull has to be opened anyway and surgeons have to map the functions of the operated area and its surrounded parts. *Electrical stimulation of the brain* (ESB) can be also used to treat chronic tremors associated with Parkinson disease, chronic pain of patients suffering from back problems and other chronic injuries and illnesses. ESB is administered by passing an electrical current through a microelectrode implanted in the brain. With chemical stimulation, a particular chemical compound is administered into a chosen part of the brain that is supposed either to stimulate or inhibit neurons within it. The least invasive methods of the stimulation methods is magnetic stimulation, called the *Transcranial Magnetic Stimulation* (TMS). TMS and rTMS (repetitive TMS) are simply the applications of the principle of electromagnetic induction to get electric currents across the insulating tissues of the scalp and skull without the tissue damage. The electric current induced in the surface structure of the brain, the cortex, activates nerve cells in much the same way as if the currents were applied directly to the cortical surface. However, the path of this current is complex to model because the brain is a non-uniform conductor with an irregular shape. With stereotactic, MRI-based control (see below), the precision of targeting TMS can be as good as a few millimetres.

However, besides the invasiveness there are other problems with the methods of direct stimulation. Intensity of an artificial stimulation can be stronger or weaker than the level of spontaneous activity in the target circuit. Therefore artificial stimulation can engage more or respectively less of brain circuitry than is normally involved in the studied function. Thus, there are difficulties in determining which brain circuitries have been actually affected by the stimulation and thus which brain structures actually mediate the studied function.

3.7.2. Electroencephalogram (EEG) data

The oldest non-invasive method to measure electrical activity of the brain is the *electroencephalography* (EEG). An EEG is a recording of electrical signals from the brain made by attaching the surface electrodes to the subject's scalp (Fig.17). These electrodes are located at exact locations of the scalp and measure corresponding activities as illustrated in table 1. EEGs allow researchers to follow electrical potentials across the surface of the brain and observe changes over split seconds of time. An EEG can show what state a person is in

(e.g., asleep, awake, epileptic seizure, etc.) because the characteristic patterns of brainwaves differ for each of these states (Fig.18a,b, Box 2). One important use of EEGs has been to show how long it takes the brain to process various stimuli. A major drawback of EEGs, however, is that they cannot show us the structures and anatomy of the brain and tell us which specific regions of the brain do what. In recent years, EEG has undergone technological advances that have increased its ability to read brain activity from the entire head from up to 128 sites simultaneously. The greatest advantage of EEG is that it can record changes in the brain activity almost instantaneously. On the other hand, the spatial resolution is poor, and thus should be combined with CT or MRI (see below).

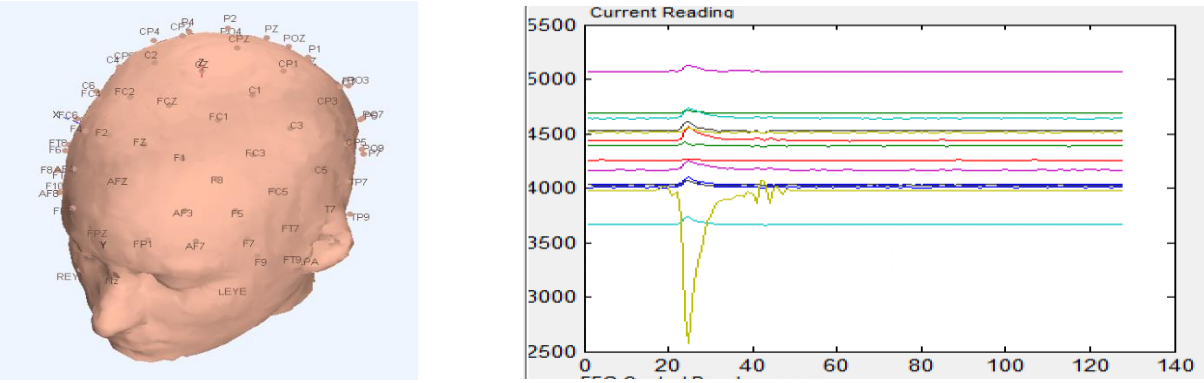

Figure.17. EEG signals taken from EEG electrodes spatially distributed on the scalp are spatio/spectro temporal data

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

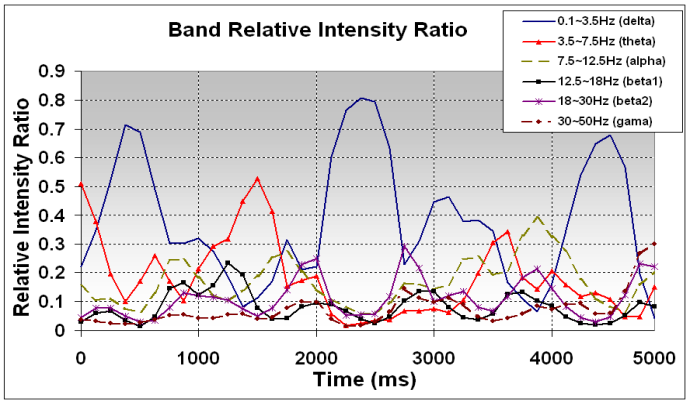

Figure 18a. Different brain waves, characterised as different signal frequencies, could have different intensity at different times and different spatial locations in the brain

Frequency band (Hz)	General Meaning
0.1-3.5 (delta)	Sleep or rest
3.5-7.5 (theta)	Learning, memory, sensory motor processing
7.5-12.5 (alpha)	Meditation, usually observed in the occipital lobe
12.5-30 (beta)	Active state, busy, or anxious thinking, concentration
30-100, (gamma)	Not known; consciousness usually 40

Figure 18b. Different brain waves are associated with different brain states.

Box 2. EEG channels, corresponding Brodmann areas (BA) and functional/cognitive activity.

EEG label	Main BA	Function
AF3, AF4	9	The frontal lobe contains most of the dopamine-sensitive neurons in the cerebral cortex. The dopamine system is associated with reward, attention, short-term memory tasks, planning, and motivation.
F7, F8	45	Together with BA 44, it comprises Broca's area, a region that is active in semantic tasks, such as semantic decision tasks (determining whether a word represents an abstract or a concrete entity) and generation tasks (generating a verb associated with a noun).
F3, F4	8	Frontal cortex. The area is involved in the management of uncertainty. With increasing uncertainty there is increasing activation.[2] An alternative interpretation is that this activation in frontal cortex encodes hope, a higher-order expectation positively correlated with uncertainty
FC5, FC6	6	Premotor cortex and Supplementary Motor Cortex (Secondary Motor Cortex) - planning of complex, coordinated movements.

T7	21	Part of the temporal cortex .The region encompasses most of the lateral temporal cortex, a region believed to play a part in auditory processing and language. Language function is left lateralized in most individuals.
T8	4	Primary motor cortex of the human brain. It is located in the posterior portion of the frontal lobe.
P7	37	Part of the temporal lobe. The temporal lobe is involved in the retention of visual memories, processing sensory input, comprehending language, storing new memories, emotion, and deriving meaning.
P8	19	Parietal cortex; Visual areas designated as V3, V4, V5 (also known as the middle temporal area, or MT) and V6 (also known as dorsomedial area). BA 19 is the differentiation point of the two visual streams, of the 'what' and 'where' visual pathways. The dorsal region may contain motion-sensitive neurons, and ventral areas may be specialised for object recognition.
O1, O2	18	Occipital cortex – Primary visual cortex V1: Vision.

3.7.3. MEG

Related method to EEG, called *magnetoencephalography* (MEG) measures millisecond-long changes in magnetic fields created by the brain's electrical currents. MEG is a rare, complex and expensive neuroimaging technique. MEG machine uses a non-invasive, whole-head, 248-channel, *super-conducting-quantum-interference-device* (SQUID) to measure small magnetic signals reflecting changes in the electrical signals in the human brain. The incorporation of liquid helium creates the incredibly-cold conditions (4.2 degrees of Kelvin) necessary for the MEG's SQUIDS to be able to measure these brain magnetic fields that are billions of times weaker than the earth's magnetic force. Investigators use MEG to measure magnetic changes in the active, functioning brain in the speed of milliseconds. Besides its precision another advantage of MEG is that the biosignals it measures are not distorted by the body as in EEG. Used in conjunction with MRI or fMRI (see below), to relate the MEG sources to brain anatomical structures, researchers can localize brain activity and measure it in the same temporal dimension as the functioning brain itself. This allows investigators to measure, in real-time, the integration and activity of neuronal populations while either working on a task, or at rest. The brains of healthy subjects and those suffering from dysfunction or disease are imaged and analyzed.

3.7.4. PET

The oldest among the noninvasive methods to study brain anatomy is *Computer Tomography* (CT). It is based on the classical X-ray principle. X-rays reflect the relative density of the tissue through which they pass. If a narrow X-ray beam is passed through the same point at many different angles, it is possible to construct a cross-sectional visual image of the brain. A 3D X-ray technique is called the CAT (Computerized Axial Tomography). CT is noninvasive and shows only the anatomical structure of the brain, not its function.

Positron Emission Tomography (PET) is used for studying the living brain activity. This noninvasive method involves an on-site use of a machine called cyclotron to label specific drugs or analogues of natural body compounds (such as glucose or oxygen) with small amounts of radioactivity. The labeled compound (a radiotracer) is then injected into the bloodstream which carries it into the brain. Radiotracers break down, giving off sub-atomic particles (positrons). By surrounding the subject's head with a detector array, it is possible to build up images of the brain showing different levels of radioactivity, and therefore, cortical activity. Thus, depending on whether we used glucose (oxygen) or some drug, PET can provide images of ongoing cortical or biochemical activity, respectively. Among the problems with this method are expense including the on-site cyclotrone and also technical parameters like the lack of temporal (40 seconds) and spatial (4 mm – 1 cm) resolution. Usually the PET scan is combined either with CT or MRI to correlate the activity with brain anatomy.

Single-Photon Emission Computed Tomography (SPECT) uses gamma radioactive rays. Similar to PET, this noninvasive procedure also uses radiotracers and a scanner to record different levels of radioactivity over the brain. SPECT imaging is performed by using a gamma camera to acquire multiple images (also called projections) from multiple angles. A computer can then be used to apply a tomographic reconstruction algorithm to the multiple projections, yielding a 3D dataset (like in CT). Special SPECT tracers have long decay time, thus no on-site cyclotron is needed, which makes this method much less expensive than PET. However, the temporal and spatial resolution of brain activity is even smaller than in PET.

3.7.6. fMRI

Magnetic Resonance Imaging (MRI) uses the properties of magnetism instead of injecting the radioactive tracers into the bloodstream to reveal the anatomical structure of the brain. A large (and loud) cylindrical magnet creates a magnetic field around the subject's head. Detectors measure local magnetic fields caused by alignment of atoms in the brain with the externally applied magnetic field. The degree of alignment depends upon the structural properties of the scanned tissue. MRI provides a precise anatomical image of both surface and deep brain

structures, and thus can be combined with PET. MRI images provide greater detail than CT images. Problems: Expense, cannot be used in patients with metallic devices, patient must hold still for 40–90 min.

Functional MRI (fMRI) combines visualisation of brain anatomy with the dynamic image of brain activity into one comprehensive scan. This non-invasive technique measures the ratio of oxygenated to deoxygenate haemoglobin which have different magnetic properties. Active brain areas have higher levels of oxygenated haemoglobin than less active areas. An fMRI can produce images of brain activity as fast as every 1×2 seconds, with very precise spatial resolution of about 1×2 mm. Thus, fMRI provides both an anatomical and functional view of the brain and is very precise. FMRI is a technique for determining which parts of the brain are activated by different types of brain activity, such as sight, speech, imagery, memory processes, etc. This brain mapping is achieved by setting up an advanced MRI scanner in a special way so that the increased blood flow to the activated areas of the brain shows up on fMRI scans. fMRI imaging technique is non-invasive and radiation-free thus providing a safe environment to the subjects involved. The images are recorded in sequence either vertically or horizontally (Fig. 19), and over time, in a matrix of intensity values. They are captured in slices through the organs, generally in 8 or 16-bit (Figure right).

The images are constructed from two components – spatial/spectral (or spatio) and temporal. The first component is identified as the volume of a brain that can be further sub-divided into smaller 3D cuboids, known as voxels (volume element). In a typical fMRI study, a series of brain volumes are collected in quick succession and the value of BOLD response at all points in a 3D grid are recorded. A general 3D brain image typically contains 10,000 to 15,000 voxels, and each voxel consists of on the order of hundreds of thousands of neurons. Spatial image resolutions can be set either to have low or high resolution. As in **Error! Reference source not found.** while high-resolution image provides more accurate information (e.g. voxels with dimensions of 1 mm x 1 mm x 1 mm) more CPU processing power is required and is not feasible at the moment. Typical spatial resolution is 3 mm x 3 mm x 5 mm, corresponding to image dimensions in the order of 64 x 64 x 30 [71] and still this resolution is relatively high compared to other imaging techniques.

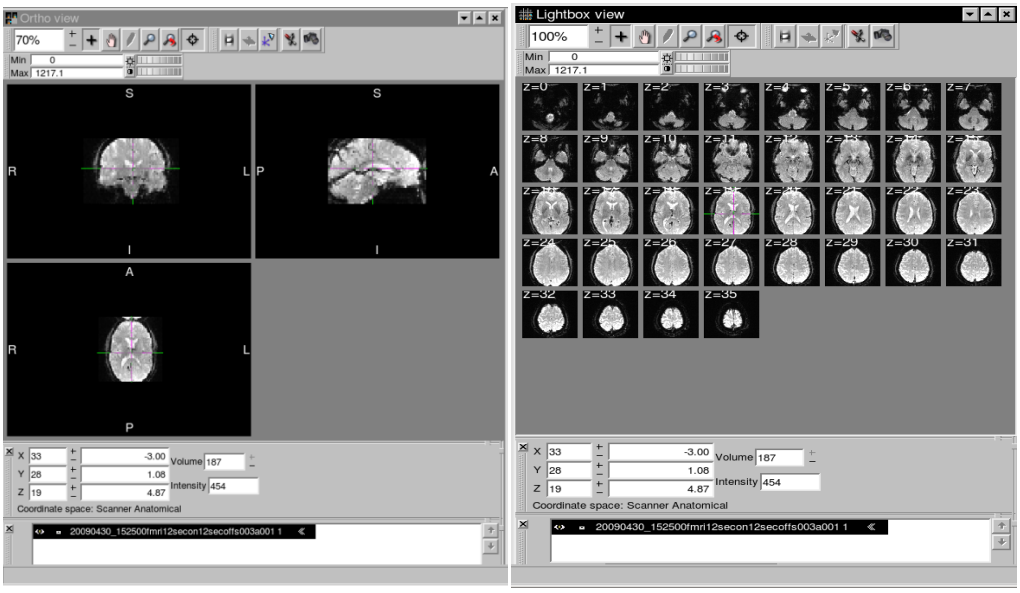

Figure 19: Brain images in vertical and horizontal slice: in sagittal, coronal and axial views (left). Slices of brain taken over time i.e. 32 images for a volume of brain (images are viewed using FSLView (FSLView, 2012) software (right) (after [76]).

The temporal component is acquired while scanning the whole volume of a brain that will take a few seconds to complete. In a single run of an experiment, 100 or more brain volumes are usually scanned and recorded for a single subject doing a particular sensorimotor or cognitive task. Temporal component depends on the time between acquisitions of each individual image, or the time of repetition (TR). In a typical experiment, TR ranges from 0.5 to 4.0 seconds and TR values in the range of 2 seconds are generally considered adequate [71]. The combination of this spatial and temporal information of the brain images will be the main concern investigated in this study.

Although a lot is known about the brain, issues about its functioning, representation and processing of information are still subjects of an intense research. The nature of brain dynamics is still unknown. Some researchers find evidence of chaos, whereas some are doubtful [73]. Main proponents of a chaotic dynamics, W.J. Freeman [74] and I. Tsuda [75], argue in favour of chaotic itinerancy based on EEG and other neurophysiological data. According to the picture of chaotic itinerancy, a complex system such as the (human) brain evolves by steps along a trajectory in the state space. Each step corresponds to a shift from one basin of attraction to another. Attractors represent classes for abstraction and generalization. Thus, the brain states evolve periodically through sequences of attractors. In a closed system the next attractor would be chosen solely by internal dynamics. In an open system, such as the brain, external inputs

interfere with internal dynamics. Moreover, due to the changes induced by learning, trajectories continually change.

The self-organized criticality state can form the basis of the brain capacity to rapidly adjust to new external and internal stimuli. State changes resembling phase transitions occur continually everywhere in cortex at scales ranging from millimetres to ~0.1 m. Local neural activity can trigger a massive state change. However, several issues of caution should be pointed out. In spite the compelling evidence for self-organized criticality in the brain, the nature of the critical state is still unknown in neurobiological interpretation. It is high dimensional, noisy, non-Gaussian, and nonstationary [74]. Tremendous physical complexity of the brain arises also from the fact that it is not a homogenous tissue. Each part of the brain is morphologically different and has its own genetic profile as can be seen by analysis of large-scale human and mouse transcriptomes. Therefore the conditions for assessment of the type of dynamics are difficult to be met. Moreover brains are open systems driven by stochastic input. Thus it seems that the brain activity hardly can conform to the mathematical definitions of chaos. Whether the term chaotic itinerancy (or any other term from the chaotic vocabulary) is appropriate to describe state transitions in brain and cortex in particular remains open to challenge.

The complex spatio-temporal activity data from the brain still awaits explanation and proper modelling and this is what other chapters of the book present.

3.8. Chapter summary and further readings for deeper knowledge

The chapter presents fundamentals of information processing in the human brain and how that can be measured as data. Some of these principles are used in the rest of the book for the development of brain-inspired spiking neural networks (BI-SNN) as the main approach here to building brain-inspired artificial intelligence (BI-AI).

The aspects of *deep learning* and *deep knowledge representation* in the brain are especially important as these principles are used as inspiration for the BI-SNN and BI-AI systems (Chapter 6) also used in other chapters of the book.

Brain data such as EEG and fMRI have been modelled using evolving SNN (eSNN) and BI-SNN in chapters 8-11,14 of the book.

More on the topic can be found in [7,38, 76]. Extended presentations on specific topics can be found in:

- Information processing in synapses (chapter 36 in [76]);
- Understanding the brain via fMRI classification (Chapter 40 in [76]);

- Modelling vision with the neocognitron (chapter 44 in [76]);
- Neurocomputational models of natural language (chapter 48 in [76]);
- Integration of large-scale neuroinformatics (chapter 50 in [76]).
- The brain and connectivity (chapter 61 in [76]).
- The Allen brain atlas (chapter 62 in [76]).

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