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Introduction to Brain-Inspired Memory and Learning Models

This chapter overviews memory and learning from four different perspectives. First and foremost, it reviews the philosophical models of human memory. In this regard, it examines Atkinson and Shiffrin's model, Tulving's model, Tveter's model, and the well-known parallel and distributed processing (PDP) approach. The chapter also gives an overview of the philosophical research results on procedural and declarative memory. Second, the chapter is concerned with coding for memory and memory consolidation. Third, the chapter is concerned with a discussion on cognitive maps, neural plasticity, modularity, and the cellular processes involved in short-term memory (STM) and long-term memory (LTM) formation. Finally, the chapter deals with the scope of brain signal analysis in the context of memory and learning. Possible scope of computational intelligence techniques on memory modeling is also appended at the end of the chapter.

1.1 Introduction

The human nervous system comprises several billions of neurons spread across the brain, spinal cord, and the rest of our body. These neurons collectively and/or independently participate in the cognitive processes undertaken by the brain. Usually, the efferent neurons receive stimuli from the receptors present in the cell membranes and carry the electrical activation due to the stimuli to the brain to recognize and interpret the stimuli. The brain in turn generates response through afferent neurons to trigger specific localized organs for its activation. Consider, for example, the experience of touching a hot body by a two-year old baby. Presume that the baby has no prior experience to touch a hot body. As she touches the hot body accidentally/incidentally, the efferent neurons present in the receptor (neurons) of her skin receives thermal stimulation, the electrical activation of which reaches her brain, and the motor command generated by the brain is then transferred to her limbs to withdraw her hand. The first-hand experience of the baby is

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unconsciously recorded in her brain, to provide her a cautionary support to avoid similar incidents in future. A natural question that appears before us is where does the baby save her learning experience? How does she automatically retrieve her knowledge to avoid similar situations in future?

The book aims at offering answers to the previously mentioned queries and the like by analysis of the acquired brain signals/images during memory formation (encoding) and memory recall stages in adults. Although very little of human memory encoding and recall processes are known till this date, it is almost unanimously accepted that the human memory is distributed in the cortex with localized activities in certain brain regions. For instance, the hippocampal region, residing in the medial temporal lobe, is found to have good correlations with relatively permanent LTM. Two other forms of short-duration memory are also reported in the literature [1, 2]. They are popularly known as STM and working memory (WM). It is known that STM can hold information for few minutes only [1–3], unless it is refreshed periodically. The WM, on the other hand, provides a support to human reasoning and apparently looks like cache memory in computer systems. It may be remembered that the central processing unit (CPU) in the computer receives and saves information from the cache while executing a program segment. Although major part of a selected program resides in the system random access memory (RAM), the cache saves only fewer bytes of storage currently under execution. The cache is designed with high speed logic circuits, such as emitter-coupled logic or integrated injection logic (I^2L) [4–6] to maintain parity in speed with the processor. Similarly, the brain performs reasoning time efficiently, which is often bottlenecked by relatively low speed LTM. The WM thus bridges the speed gap between human reasoning system and the LTM access, which usually is sluggish with respect to our speed of logical reasoning.

The book is all about WM and STM encoding and recall, with a small coverage on interactions between the WM and the STM. Although there is a magnificent reporting on memory encoding and recall, most of the research outcomes are based on behavioral experiments on humans [7]. Thus the existing research results cannot offer the cognitive basis of memory encoding and recall. With the advent of modern brain imaging and signal acquisition equipment, it is now possible to make a thorough study on memory encoding/recall processes. Although such study provides a more scientific basis to understand the memory encoding and retrieval processes, they too are not free from limitations. For instance, the existing non-invasive techniques mostly rely on scalp potential and thus can hardly capture single neuron activation. So, the analysis is undertaken on the local response of a group of neurons. Second, while administering memory activity, the other activities of the neuron also appear on the scalp and thus act as noise input to the memory study. Elimination of the noise is not easy here as the noise distribution often falls in the same frequency spectra used by the memory system.

The mystery of memory formation largely relies on the regulatory and control mechanism of the cellular proteins. A brief review of molecular biology reveals that the neuronal cells, like any other cells in the human, contain deoxyribonucleic acid (DNA) double helix comprising several millions of four bases (adenine [A], guanine [G], thymine [T], and cytosine [C]). These four bases have an apparently random (positional) occurrence in the individual string of a DNA. Small sequences of such bases on the DNA that are responsible for inheritance of genetic materials from parents to children are called genes. The neuronal cells containing DNA double helix thus contain genes, which often translate to form cell proteins. The protein formation by DNA and particularly genes is a two-step process. In the first step, the DNA translates to ribonucleic acid (RNA), and in the second step, the RNA transforms into proteins. These cell proteins help in permanent/semi-permanent encoding of the acquired information in the LTM. How the protein help in encoding is a complex biochemical process, very little of which is known at present.

This chapter is organized into 11 sections. In Section 1.2, a philosophical survey to memory is undertaken. Section 1.3 is concerned with the brain-theoretic interpretation of memory formation. This section also takes into account the experimental perspectives of memory and learning. It includes both surgical and therapeutic experiments on memory encoding by considering plasticity and stability issues of memory and learning. Sections 1.4, 1.5, 1.6, 1.7, and 1.8 are concerned with cognitive maps, neural plasticity, modularity, and the cellular process behind STM formation and LTM formation, respectively. Section 1.9 deals with brain signal analysis in the context of memory and learning. Section 1.10 examines the scope of mathematical/computational models of memory and learning. Section 1.11 reviews the scope of the book. This section also provides a summary of the work presented and future directions of research in memory and learning.

1.2 Philosophical Contributions to Memory Research

Among the early contributions in memory research [8–15], the works by Atkinson and Shiffrin [8] and Tulving [9] need special mention. The PDP approach to imitate natural learning by artificial neural networks, enunciated by Rumelhart and Hinton [10, 11], also had a good impact in the late 1980s. In addition, there exist key contributions to memory research, concerning (mental) rotation of imagery in memory. In this regard, Kosslyn's work on mental imagery [12, 13] studies needs mentioning. The role of memory in comparing relative object size with imagery also is important. Reed's work on part–whole relationship in mental imagery also gave a good impetus to memory studies. In this section, an overview of the philosophical issues to memory research is presented next.

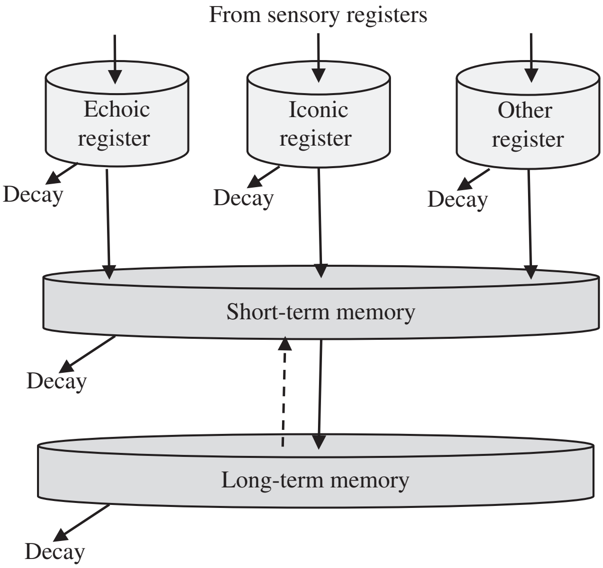

Figure 1.1 Atkinson–Shiffrin's model of cognitive memory.

1.2.1 Atkinson and Shiffrin's Model

Atkinson and Shiffrin proposed a hierarchical model of memory [8], comprising three layers, as depicted in Figure 1.1. The input layer represents sensory registers, which acquire information from the real world by three different modalities. The sensory registers are named according to the modality of their usage. For example, iconic register refers to visual information, the echoic register keeps track of the audio cues, olfactory register takes care of aroma of the stimulus, and the like. The registers can hold information for few seconds only, and they need to be refreshed to store new real-world information. Thus the sensory registers primarily acquire dynamic information.

Before the registers are refreshed, the information from the sensory registers is transferred to STM to hold it for several minutes. Finally, with repeated trials the information from the STM is transferred to LTM for permanent storage. Two fundamental aspects of Atkinson–Shiffrin's model are (i) natural decay of memory information both at sensory register and STM levels and (ii) provisions of feedback from the LTM to the STM.

Although Atkinson–Shiffrin's model received high appreciation for its pioneering contributions, it too is not free from limitations. For example, consider the following case history. In a bike accident, the person's left side of the cerebral cortex was damaged, causing a severe malfunctioning in the STM. However, the person's LTM could continue memory encoding and recall even after the accident.

This naturally questions the architecture of Atkinson's and Shiffrin's model. The natural question is how does the person update his LTM without using the STM? Consider a second case study. In order to cure serious epilepsy, a part of the temporal lobe containing the hippocampus was removed. After the surgery was over, the person was found to have lost the power of encoding in the LTM but could retrieve well most of the past information before his surgery. Two questions here become apparent. First, if the hippocampus is removed, how does he retain his LTM? Second, in case the LTM prior to his surgery could retrieve many of his past information, why he cannot encode new information into the LTM after the surgery? The first question cannot be answered following Atkinson–Shiffrin's model. However, the answer to the second question is apparent following the Atkinson–Shiffrin's model, which claims that the feedback path from the STM to the LTM might have been damaged.

1.2.2 Tveter's Model

Tveter proposed an extension to the Atkinson–Shiffrin's model, which overcomes some of its shortcomings [16]. For example, in the bike accident problem referred to earlier, the updating of the LTM in the absence of the STM can be explained by Tveter's model. In a recent study [17], Tveter indicated a feedback path from the LTM to the STM and two alternative forward paths from the STM to the LTM, as shown in Figure 1.2. The first path from the STM to the LTM is used for decision making with incoming information into the STM, while the second alternative path is used for long-term storage in the LTM.

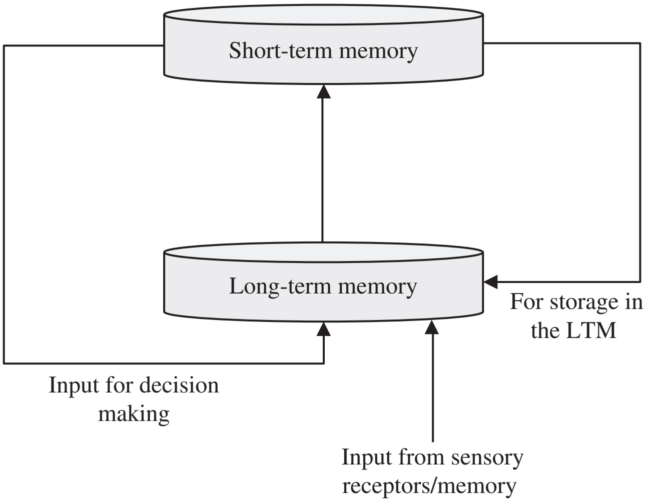

Figure 1.2 The architecture of Tveter's model.

1.2.3 Tulving's Model

Tulving proposed a hierarchical model of three-stage memory [18], where the first stage, located at the top of the memory hierarchy, refers to episodic memory. The second stage, located at the second level of the hierarchy, is called semantic memory, and the third stage, located at the bottommost layer of the hierarchy, is called procedural memory. The episodic memory in Tulving's model stores episodes (i.e. incidents that take place in individuals' personal perspective). The semantic memory derives relationship among connected (shared) episodes, whereas the procedural memory extracts and saves procedures (sequence of steps) to solve a complex problem from the semantic interrelationships about events/episodes.

Consider, for example, the experience of a child about rain and its precedence relationship with dark cloud. The child experiences the temporal precedence of the dark cloud to occurrence of rain and gradually learns the interrelationship between the two episodes. At a first glance, the child saves the two episodes independently in the episodic memory. Then with repeated occurrence of the temporal precedence of the dark cloud to rain, she/he learns the semantic relationships between the two episodes. Suppose, she/he further experiences of having city roads flooded with water due to severe rain and notices people to arrange opening of the blocked drainage system by devices like brush and sticks. The child may derive the procedure of cleaning the water-drainage system and saves it in his/her procedural memory. The most interesting part of Tulving's model is hierarchical representation of memory, where a direct pathway from episodic to semantic to procedural memory exists in the memory hierarchy, and occurrence of the current episodes when matched with pre-stored ones reminds the subject about the procedures he/she needs to adopt to handle the present circumstance. Figure 1.3 provides a schematic overview of the memory model following Tulving's postulates.

1.2.4 The Parallel and Distributed Processing (PDP) Approach

Rumelhart and Hinton in the 1980s pioneered the art of parallel and distributed approach of neural signal processing in the context of learning and memory [11]. In their basic framework, they considered a feed-forward topology of artificial neural network with provisions for supervised learning. Supervised learning usually refers to learning the interconnectivity among a set of neurons to satisfy a given set of externally generated training instances, comprising the input and output attributes of episodes/observations/experiments. The PDP approach keeps provisions for simultaneous learning of a number of neurons placed in layers based on the measure of an estimate of error at the neurons in the output layer.

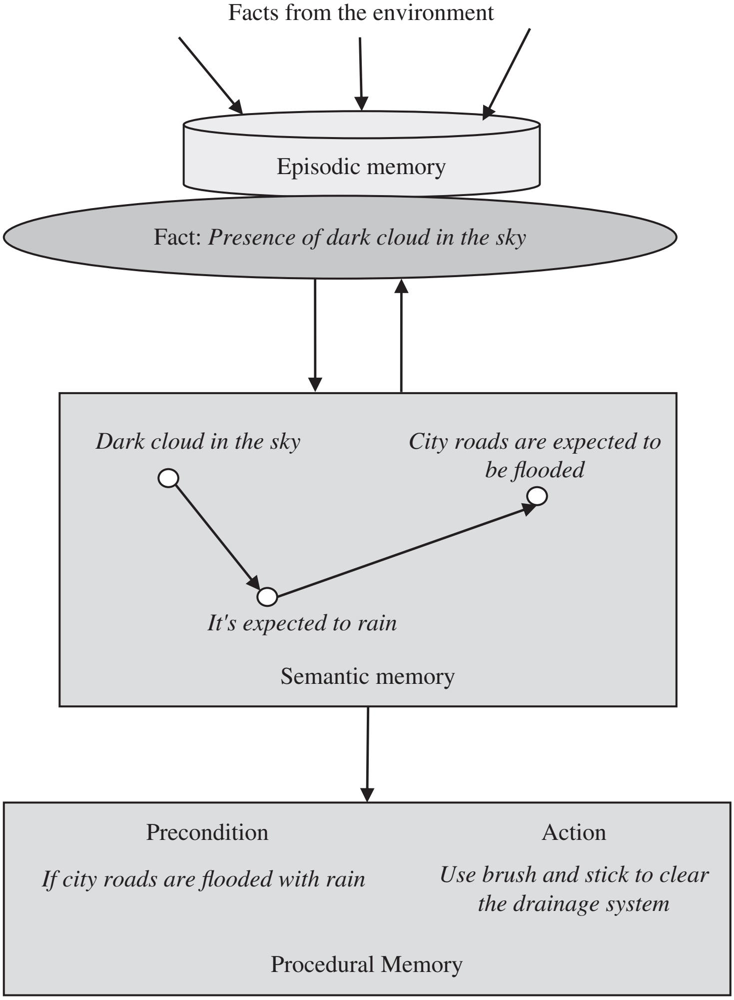

Figure 1.3 The architecture of memory hierarchy in Tulving's model.

The error values at the neurons in the output layer represent the difference of the computed signals from the desired (targeted) signals at the respective neurons, which are propagated backward to adapt the synaptic connection strengths (weights) between neurons of two layers. The policy, well-known as error back-propagation, is naïve in the sense that it can quickly adjust layer-wise neural connectivity with an aim to produce the targeted outputs from the measured values of the input instances of the training data set. Such process of adaptation of weights/neural synaptic connectivity is continued until the error value at the neurons in the output layer of the synthetic neural network goes below certain threshold, also called error-limit. Naturally, when the training algorithm terminates, the strength of synaptic connectivity between neurons of one layer to the next converge, indicating stable layer-wise interconnections to remember the complete set of training instances.

The PDP approach apparently mimics the biological process of neural learning particularly for two specific types of problems. First, it demonstrates a general approach to attack the problems of supervised pattern classification by remembering input–output training instances in the form of neural connectivity. Once the network is trained, i.e. the interconnection weights are extracted for a given set of training instances, the network allows generalization, so as to predict the output for an unknown input instance close to one of the known input instances. Second, it offers a new avenue to develop functional mapping between the input and output instances, particularly when the outputs involve nonlinearity of high orders of the input attributes. In fact, in many real-world problems, the true functional form between the input and output is not clearly known. One typical example is the user's response in a nuclear power plant [19]. It is known that the electrical power output in a nuclear power plant is proportional to the neutron population liberated from the thermonuclear pile. Usually, a neutron-absorbing rod is inserted into the thermonuclear pile to control the neutron population. The skilled workers usually have a good experience to determine the rate of withdrawal or rate of insertion of the neutron absorbing rod into the pile. Here, the electrical power output is a highly nonlinear function of the parameters: rate of insertion, rate of withdrawal, depth of insertion, and the like, which is difficult to model analytically. However, given the training instances for the problem, it can be easily captured by the proposed neural framework with the help of supervised learning. So, PDP approach might serve a solution to the problem.

1.2.5 Procedural and Declarative Memory

Several theories of memory systems and learning are prevalent in the literature. Of these theories, one most prominent mechanism of learning and memory refers to the work by W.R. Klemm [20, 21]. According to Dr. Klemm, there are two different kinds of memory, called declarative memory and procedural memory. The declarative memory generally operates in conscious mode of the subject, whereas the procedural memory often develops subconsciously. For instance, declarative memories include memorization of concepts and facts, rules of procedures, words and notes of songs, or anything else that humans memorize and recall consciously. As people need to consciously access declarative memories, these memories are called *explicit memories*. Procedural memory, on the other hand, deals with cognitive or motor skills that humans develop after several sessions of practicing. For instance, to play a piano, or basketball, humans need to develop their motor skills through several practices.

Surgical lesions in animals indicate that there exist specific neural structures for explicit memory, involving the medial temporal lobe, in particular the hippocampus. General observations in humans in presence of naturally occurring brain diseases also confirm the previously mentioned phenomenon. Besides the hippocampus, the other brain modules that too participate in forming key brain structures include entorhinal, peripheral, and para-hippocampal cortices. Among other important structures in the brain that seem to participate to develop explicit/declarative memory includes anterior thalamic nucleus and medio-dorsal thalamic nucleus. It is presumed that these structures and their interconnections with their neo-cortex help in developing explicit memories by binding different areas of the neo-cortex to serve both perception and STM of different events. It is noted that the neo-cortex has the capacity to support LTM even without utilizing medial temporal lobe and the mid-line structures.

To recognize the importance of the hippocampus in STM formation, David Olton and Robert Samuelson [22] undertook an interesting experiment. The experiment involves lessoning of the hippocampus and then placement of rats in a maze with multiple radial arms of the maze with food containers placed at the end of a few arms. It is noted that rats with their hippocampus lesion continued moving over the same arms several times, as they fail to remember the visual representation of the appropriate locations of the food items. Porkin, in one of his early experiments, refers to a subject with wounds in the hippocampal and temporal part of the brain. He noticed deficits in the formation of declarative memory but a little impairment of procedural memories.

As reported by Klemm [21], people with a damage in the cerebellum and/or other motor control regions of the brain have limitations in forming procedural memories, although their declarative memory remain relatively intact. The interconnection/sharing of procedural and declarative memory with learning is illustrated in Figure 1.4. It is apparent from Figure 1.4 that humans undertake conscious effort to save sensory information and their contextual counterpart in declarative/conscious memory. On the other hand, the need-based motor movement that often appears relevant from the contextual analysis of sensory data triggers motor learning requirement. The motor-learning schema and condition that humans develop by natural practicing are saved in procedural memory, as indicated in Figure 1.4. The procedural memory, presumably, evolves from repetition/rehearsal of declarative memory processes.

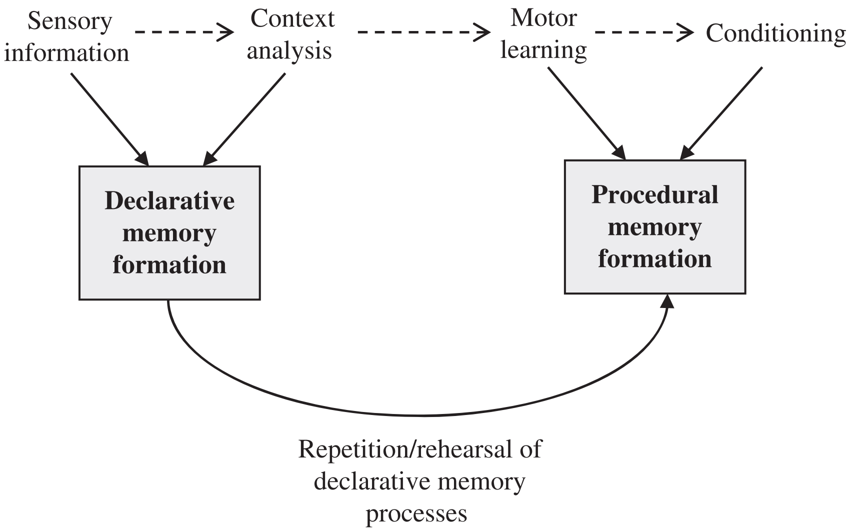

Figure 1.4 The interconnection between procedural and declarative memory.

1.3 Brain-Theoretic Interpretation of Memory Formation

Memories exist in different forms and rely on distinct neural systems. In the last two decades, a great progress has been made in the understanding of the biological basis of memory formation. The identification of mechanisms necessary for memory consolidation and reconsolidation, the processes by which the pre-training and post-retrieval fragile memory traces become stronger and insensitive to disruption, has indicated new approaches for investigating and treating psychopathologies. A few of the key biological mechanisms are explained in this section.

1.3.1 Coding for Memory

The human brain processes external stimuli to encode relevant and useful contextual information in the brain by a complex electrochemical process. It is interesting to note that there exists coincidence between the memory recall process and synthesis of electrical spikes by the brain at relevant brain lobes/regions. Klemm [21] and Purves et al. [23] at the conclusion that the neural circuits responsible for synthesizing electrical impulses during the memory recall process are spread widely across the brain and are not limited only in the sensory processing area, such as auditory and/or visual cortex.

In case the firing patterns are of sufficiently stronger amplitudes and prolonged, a few synapses are strengthened, thereby activating certain genes in those neurons. The activation of the gene creates biochemical changes, required to preserve the experience due to synaptic strengthening. The most important part in memory research, perhaps, is the mechanism of the retrieval process from the memory. It's a natural question whether the same impulse patterns that were used for memory encoding are regenerated during memory recall. Another question often arises is that whether the same circuit impulse patterns are generated during multiple learning of similar information. Our daily experience reveals that humans hardly require any stimuli to recall the desired information. The previously mentioned experience in turn raises one additional question: does the brain by natural means generate the same series of impulses during memory recall? Recent study on memory encoding and recall answers a few of the mentioned questions.

Gelbard-Sagiv et al. [24] in one of their recent papers indicated that during free recall, the original impulse patterns, which are used to encode in the hippocampal region, are reproduced. Several studies reveal that the hippocampus and its adjacent area in the medial-temporal lobe is responsible to learn events in a specific way, depending on selected features of the stimuli, on the category of the stimuli, and also on the individual people and/or relevant landmarks. The responses of the hippocampal region usually last for longer durations than that of the stimuli. One common question that naturally appears is as follows: how the sequential responses to successive stimuli or episodes are produced by the brain? Experiments undertaken on subjects having intractable epilepsy, with electrodes implanted to localize the source of epilepsy, during learning with memory recall, offer an interesting evidence in this regard. Subjects are presented with audio-visual clips and the single neuron responses are recorded during the phase of subjective understanding and learning of the clips. Next the subjects are asked to recall the images and again the single neuron responses are recorded. It is noted that during subjective learning phase, a few neurons participate only for selected video-frames. In other words, the same neuron may not participate in the learning process of two different video clips. It is interesting to mention here that during the recall cycle of the audio-visual frames, the same neurons that participated during the encoding of a given frame also participates in the recall process of the same frame. Additionally, it is observed that during free recall cycles of the clip sequences, the reactiveness of the same hippocampal and entorhinal cortex takes place with similar firing patterns as that of the learning phase. In the previously mentioned analysis of firing patterns, the number of impulses generated at successive time-intervals, before, during, and after offering an episode in the movie clip, are recorded. This apparently means that the core, if any, used to register the information in the memory, must have been used again during memory recall. The functional magnetic resonance imaging (fMRI) studies undertaken also confirm that the brain-activity patterns remain similarly localized in spaces during both encoding and memory recall cycles.

In the preceding analysis, the experiments are conducted around the hippocampal region with an understanding that the hippocampus plays a major role in LTM and also partly in STM encoding and recall. Here, the subjects are advised to recall the audio-visual clips after five minutes, counted from the offset of the stimulus (audio-visual clips). Naturally, five minutes is a very small time to form a permanent LTM. So, the preceding results and conclusions are based on the assumption of the hippocampal networks' participation in the STM formation and recall.

1.3.2 Memory Consolidation

Humans like other mammals naturally save extracts of STM into long-term storage through a process of memory consolidation. In the absence of memory consolidation, new experiences may be recalled only within few seconds or maximally one to two minutes. Certain biochemical processes are needed to transform STM into a long-term storage. The biochemical representation then is expected to be reflected in permanent changes to the gene expressions. Until now, this remains a virgin area of research cognitive neuroscience.

Klemm [21] finally arrives at the conclusion that memory consolidation process is built through memory access processes for storage and retrieval. The STM receives inputs through interaction from real world for a very short duration of the order of few seconds. Typically, information from the STM can be retrieved within minutes of its encoding in STM. The memory consolidation process transfers information from the STM to the LTM, as depicted in Figure 1.5. The memory access system that receives input from both the STM and the LTM, sometimes transfer information to the STM, when the information is used as WM elements for reasoning.

Although the hippocampus is responsible for long-term declarative storage, apparently it is not a place for memory-storage site. Several studies conducted in the past reveal that forgetting information usually is a matter of faulty retrieval. Faulty retrieval here refers to the presence of information in the memory, although their accessibility in absence of the right cue is questioned. Like memory encoding, the retrieval often occurs both consciously and subconsciously, and very little about the distinguishing retrievals is known till the date.

To understand the memory consolidation process, let us take few examples. When a person dials a telephone number after having it from the telephone directory, he remembers the number for a few seconds in the STM, here referred to as "working memory." Unless the person dials the same number several tens of times, he hardly remembers it permanently. Consolidation of memory thus requires several practicing before it is saved in LTM permanently.

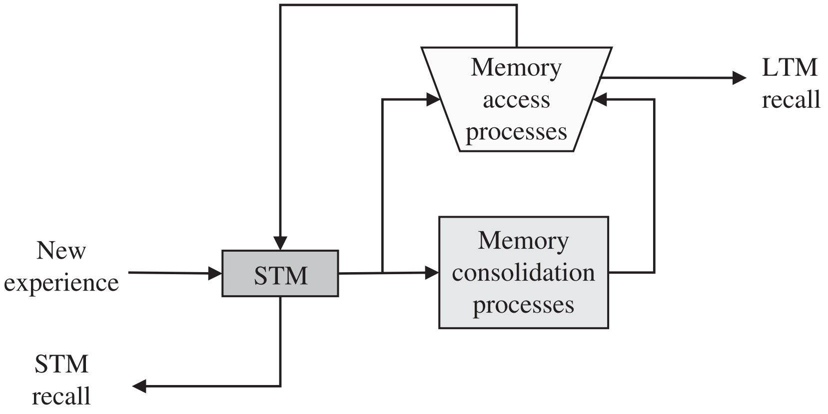

Figure 1.5 The interconnection between STM and LTM through memory consolidation process.

Another example of memory consolidation is studied on rats. The experiment includes placing a rat inside a maze with electrified surroundings. As the maze is open, the rats attempt to move out of the maze. However, while crossing the maze, it may hit the electrified side-walls and temporarily saves the topology of the surroundings in its STM. Even if this is a single-trial experiment, the rat remembers it and won't make an attempt to come out from the cage.

Korman et al. [25] and Yoo et al. [26] in two independent studies emphasized the scope of memory consolidation during sleep. They examine the single-electrode recordings from four different regions of neo-cortex of primate. They noticed that the learning experience of the last day was replayed during sleep in the form of similarity in electrical spiking in the same regions of the neo-cortex. The preceding experimental result opens up a new mystery that humans undertake memory consolidation during sleep. A second study by other research groups [21] undertaken on rats exhibits a similar replay of synchronized neuronal firings in hippocampus and neo-cortex during non-grieving sleep in comparison to that happened during the wakeful condition.

Sleep has different stages. It is noted from experiments that slow-wave and dream sleep both contribute to the processes of memory consolidation. However, slow-wave sleep, particularly the stage-2 sleep is most important for memory consolidation process. It is observed that the duration of stage-2 sleep declines with aging, which perhaps gives an explanation in declination of memory activity of elderly people. Many psychologists are of the view that during sleep stages, the brain makes attempt to replay the learnt experience (particularly the rewarding and the fierce ones). Thus the replay process during sleep helps strengthening the synapses, which participate in the formation of memory. Another contemporary theory reveals that sleep increases the signal-to-noise ratio of the memory by suppression of unwanted synaptic activity due to noisy external signals in our daily life.

A common question that often arises is about the location of memory. It is known that visual information are stored in the aromatic region, the audio information in the temporal region, and the aromatic information in the olfactory region of the brain. When we retrieve information about a beautiful flower, the brain recalls them from different modules of the cortex. For example, the aroma of the flower is recalled from the olfactory lobe, the beauty of the petals is recalled from the occipital lobe. Then how the complete information about the flower concerning its aroma and beauty jointly appears in our mind? This is due to the phenomenon that there exists a "Central Memory Manager," which integrates the recall activity across different lobes of the brain to present ourselves complete information about the flower. The consolidation process for multi-factored perceptual information is still an open area of research, and the control policy to retrieve them jointly is another virgin arena of modern memory research.

Many brain scientists emphasize the importance of synchronous oscillations at different lobes, thereby providing a possible interaction among the lobes in the process of encoding and recall of memory activity. Osipova et al. [27] demonstrate through experiments that the brain signals undergo oscillatory response while encoding and recalling of declarative memory for pictorial stimulus in the human. The research team observes that prominent γ activity (60–90 waves/s) takes place in the occipital areas. They also observe that θ activity (4–9 waves/s) increases at the right temporal hemisphere. Unlike pictorial stimuli, word stimuli are used to note the θ activity in the same brain region. Another important field of study in memory research includes the issue of coherence. Klemm in his research papers [21] examines coherence in electroencephalography (EEG) signals in multiple frequency bands when human subjects observing ambiguous figures as happen in illusion, suddenly recognize/remember the alternative image. The synchronization of the EEG signals in different lobes of the brain has shown memorization of words as synchronized θ frequency oscillations (4–7 waves/s) between the hippocampus and entorhinal cortex [28].

1.3.3 Location of Stored Memories

Karl Lashley in 1920s [29], undertook a series of experiments to determine where the brain stores learnt information. It is found that rats after learning a task can retrieve the information, even if the neo-cortex is partially damaged before the recall. This indicates that regional lesion does not impair the memory, irrespective of the region of the cortex is damage.

Broca, in 1861, identified the early speech center. In 1874, Wernicke suggested that language processing memories are localized to specific genes in the left hemisphere (LH). It is now known that these “centers” are not only connected to each other but are part of larger circuit as well involving other brain regions. Several studies have been undertaken by E. Roy John and his team to study the distributed nature of memory encoding and recall by utilizing the electrical signatures of the brain. Johns’ research echoed the possible synchronization of brain signals in both frequency and phase to distribute encode and recall information. The positron emission tomography (PET) and magnetic resonance imaging (MRI) scan studies also lead to the same conclusion that memory is a parallel and distributed process that rely on the population of a number of neurons across the brain. Hubel and Wiesel and their followers in their work [30] indicate that during visual encoding, a few neurons in the visual cortex participate to encode color, a few to movement, a few to shape and line orientation, and other features of an image, describing an object. Neurons of these areas hold visual representations in WM for a short duration, even after the stimulus is withdrawn. It is indeed important to note that retrieval of information need not necessarily be the same site, where the information is stored.

1.3.4 Isolation of Information in Memory

During the regular day-to-day activities, human often come across similar episodes with overlaps between the episodes. How do humans recall and distinguish similar episodes from their encoded information in memory? The segregation of information is part of brain’s autonomous power of control and thus highly relies on the hippocampal region. In rodents, individual neurons in two distinct regions of the hippocampus (the dentate gyrus, CA-3 regions) selectively generate a sequence of impulses that encode distinct features of the stimulus in non-overlapping circuits [31]. For instance, the hippocampal place cells exhibit unique electrical patterns to similar but different location cues in the CA-3 region. However, neurons in the CA-1 region are insensitive to these differences. Bakker and his teammates [31] employ high resolution (1.5 mm) fMRI to demonstrate that activity responses to stimuli indicate non-overlapping segregation in the hippocampal region as found in rodents earlier. In Bakker’s experiment, the fMRI scanning of the subject is undertaken, while observing an unknown image. The same image is repetitively presented in its subsequent turns after presenting 30 different images. It is noted that brain-activity is more prominent during the first time presentation of an image in comparison to the same during the subsequent presentations. The apparent justification of this is due to engagement of fewer common resources to process information the brain has previously experienced. One magical observation appears in Bakker’s experiment, when the second stimulus presented is similar with its occurrence but not identical. Under this circumstances, the second image is treated as a new experience with the same level of response as happens to him for the first stimulus. It is indeed important to mention here that the previously mentioned effect is observed only in the hippocampal region, the dentate gyrus, and the CA-3 region. Further studies reveal that the neurons in the dentate gyrus respond to selective details of a visual image and that it receives from the entorhinal cortex and projects them over the CA-3 region. The projection segregates lasting memories to test having possible similarity in related stimuli presented subsequently. In case the new image has no matching with any of the preceding ones, the stimulus is treated as new, an additional neuronal resource is employed to create a memory for the new input.

1.4 Cognitive Maps

Humans often represent relative distance between pairs of locations in their mental map, located in the hippocampal region. This mental map helps human to determine direction, such as left or right, top or bottom, and the like to describe location of an object in a fixed frame with respect to another object. In brief, cognitive maps refer to the internal representation of our spatial environment. Such mapping includes relative directions/locations and distance among objects on a small space as over a table and distance/direction among cities on a large scale as well.

Until now, it is not clearly known whether cognitive maps are encoded in a logical sense or by numerical means. Most of the researchers in cognitive science are of the view that cognitive maps are coded to describe both analogical and logical (proportional logical) phenomena [32–34]. Thus according to the researchers, our mental map for a city includes both picture like images of the relationship among streets and buildings and logical proposition such as "The Ganges meets the Bay of Bengal in the southern part of West Bengal." Information in the cognitive map thus offers us the interrelationship between objects and their images and/or spatial relations between pairs of objects. Occasionally, cognitive maps are used to describe procedural knowledge, such as "To see the Tajmahal, one has to visit Agra, which is approximately six hours journey from New Delhi."

Cognitive maps represent relative distance between cities without referring to direct numbers such as 100 km or 200 miles but can scale the distance between pairs of cities, indicating which distance is longer compared with other distances between pairs of cities [35]. Thorn Dyke undertook an interesting experiment to study the mental power of people to remember the relative distance between pairs of cities. Participants in this experiment alternated between study and recall trials until they could accurately reconstruct the cognitive map on two consecutive trials. Given a scale, such as 1 km = 1 in., the participants are asked to determine the distance between 64 possible city pairs, presented on a sheet of paper and are instructed to measure the approximate distance in kilometer between each pair of cities. It is noted that the participants in most cases have small error, less than 5%, indicating that they can remember the relative distance between pairs of cities and also are capable to measure the absolute distance based on the given scale.

McNamara et al. [36] used an intelligent approach to obtain distant estimates. The fundamental postulates that McNamara proposed is quoted as follows: “Psychologists should use task that minimize demand characteristics in order to assess the properties of mental representation more accurately” [37]. McNamara observed that mental images usually are hidden and covered, and they wanted to make these processes overt and measurable. However, the methods they adopted to make these processes overt might not accurately reflect the covert processes.

1.5 Neural Plasticity

Most psychologists believe that old people cannot learn from new trials as learning ability generally diminishes with age. However, it is our daily experience that older people too often augment their knowledge from their daily experiences. This naturally indicates that those people still have plenty of unused network capacity. Neuro-scientists, generally characterize this learning ability of the network as plasticity. Generally, an adult has as many as billions of neurons in his/her brain, each being connected with several hundred other neurons through synaptic cleft. When the subject desires to learn additional information, additional synaptic connections are developed between pairs of existing neurons, where the new connection refers to new addition of information in the brain. In other words, brain networks are plastic, i.e. it can accommodate changed information. For example, people who get new bi-focal or tri-focal glasses have to learn to adjust to the changed sensory experiences. Eventually, the new way of looking at things becomes natural due to additional rewiring/connectivity in the visual cortex circuits. The formation of new synapse takes place because of significant reduction in dendritic spines (little outgrows of dendrite membrane, where synapses develop). The reduction in dendritic spines is generally noticed in nervous system, if the sensory pathways are blocked during embryo-genesis or during early post-natal life.

Our interesting and unexpected findings [21] in neural systems that need special mention are that the topological maps are not necessarily fixed. There are many evidences that the topological maps are modified by experience and neural input conditioning and thus are different for differing individuals.

The learning ability and change in synaptic connections in old-aged people degrades because of faulty consolidation of the STM. Experiments with older animals confirm that they have no trouble to perform old learnt behavior but have difficulty in the consolidation of new learning experiences. It is noticed that in humans too, old-aged people usually can remember their classmates promptly, but often they fail to answer whether they have taken their breakfast. The neuro-psychological interpretation of such forgetfulness of STM is due to limited number of active neurons in the brain, as fewer neurons survived and many of them are not replaced. However, the remaining neurons can generate axonal and dendritic processes and thus can create new synapses.

1.6 Modularity

Modularity refers to specific functional attachment to neurons. Neurons collectively form a module to participate in specific cognitive tasks. The participating neurons are not always localized in the same place. The module formation or specialization of neurons is partially autonomous, but as they are interconnected, they influence and also get influenced by other modules. The anatomical and functional boundaries among modules usually are fuzzy, and occasionally the neurons in one module at times are recruited to participate in the functions of other modules.

Recent studies on brain-imaging offer an interesting explanation of modularity [38]. Among the modular functionalities of neurons, morality is given special consideration. Morality generally arises from the interaction between emotion and logic. However, moral judgment, which is a mixture of both emotion and logic, is controlled from a specific region of the brain (prefrontal cortex). Greene et al. [39] demonstrate that when people encounter moral dilemmas, the parts of the brain that light up depends on whether emotion and/or impressionable logic are most involved. However, when people, such as criminals, pretend to have abnormal behaviors, they may lose the emotion triggered decisions and use their logic to satisfy their decisions.

1.7 The Cellular Process Behind STM Formation

The STM formation is a complex process concerning repeated triggering of the participating neurons, connected in tandem/parallel by sensory stimuli. When sensory stimuli appear to a neuron, certain biochemical processes (to be presented shortly) are activated resulting in larger action potentials of prolonged duration. The large action potential enhances the mobility and momentum of the Ca^{2+} ions in the post-synaptic region of the neuron. Because of high mobility and momentum, the vesicles containing the neuro-transmitters are ruptured due to striking of the high energy Ca^{2+} ions. Consequently, the neuro-transmitters are released from the vesicles, and chemical signal transmission is continued to the next neuron connected in tandem with the post-synaptic region of the previous neuron.

When excitatory neuro-transmitters (acetylcholine [Ach] and dopamine [DA]) are released at the post-synaptic region of a neuron, the subsequent cells in tandem are excited positively with higher action potentials in the subsequent neurons. When inhibitory neuro-transmitters, such as γ-amino butyric acid (GABA) is released, the subsequent neurons connected in tandem block the further propagation of neuro-transmitter to inhibit the synaptic activity of the neurons in chain form. As already indicated, the amplitude of action potential enhances the release of neuro-transmitters, similarly the increased width of action potential continues releasing of neuro-transmitter for longer duration. The cellular biochemical processes enhance the width and amplitude of action potentials of neurons by a series of interlinked activities. Animal experiments have been conducted to check the learning of electrical shocks in STM. The following steps are undertaken to learn STM formation in presence of electric shock to *Aplysia*:

1. With the onset of electrical shock to the skin of the animal, serotonin (hereafter called 5-HT), a modulatory neuro-transmitter, is released from a distinct class of interneurons (IN), also called facilitatory neurons.
2. The facilitatory neurons, in turn, regulate the characteristics of sensory neurons (SN) and the strength of their connections with postsynaptic interneurons and motor neurons (MN). This process of regulating post-synaptic behavior is called hetero-synaptic facilitation [40].

   The molecular mechanism describing the short-term hetero-synaptic facilitation includes the following sub-steps:
   (a) Serotonin binds to several types of G-protein-coupled receptors present in the membrane of sensory neurons (SN). These receptors when activated develops two predominant signaling cascades in the sensory neurons (SN).
   (b) The first signaling cascade refers to the cyclic adenosine mono-phosphate/protein kinase A (cAMP/PKA). The second signaling cascade refers to diacylglycerol/protein kinase C (DAG/PKC) cascades [40].
   (c) The PKA and PKC in turn affect the spike waveform and its excitability of the SN. In fact, activation of PKA and PKC cascades modifies different K^+ channels, leading to an enhanced spike activity and broadening of action potential. Thus, injection of larger extrinsic current into the cell maintains longer activity of sensitization, thereby memorizing the stimuli for longer duration in STM.

1.8 LTM Formation

LTM formation generally requires long training of tens of hours for permanent encoding of the desired information or stimuli in the brain. Fundamentally, STM and LTM formations have many commonalities from the point of view of neuro-transmitter release and signaling characterization inside the synapse. However, there exist a fundamental difference between STM and LTM encoding. In LTM encoding, particularly in the consolidation phase, gene transcription is required to prepare desired cell-proteins, which in turn causes changes in the specific genes, thus maintaining performance of the desired information in the LTM. Phenomenologically, repeated training of the neurons enhances the phosphorylation process of the transcriptional activator CREB1 (cAMP responsive binding protein 1). CREB1 binds to a regulatory region of genes, known as cAMP responsive element (CRE). While CREB1 participates as an *activator* in the gene transcription process, CREB2 acts as the *repressor* of gene transcription. The repression activity in the transcription process, however, is suppressed by MARK phosphorylation.

The importance of transcription factors in LTM formation is not only limited to the induction phase. Consolidation phase here corresponds to the time-window, during which RNA translation and protein synthesis take place to transform STM to LTM. For instance, the treatment of ganglia with five pulses of serotonin (5-HT) over a period of one and half hour leads to binding of CREB1 to the promoter of its own gene, resulting in an induction in CREB1 synthesis. It is noted that prolonged RNA and protein formation for long-term facilitation persist for at least 10 hours after induction. The previously mentioned experimental results indicate a positive feedback of CREB1 to regulate its own level of expression supports memory consolidation [41].

1.9 Brain Signal Analysis in the Context of Memory and Learning

To understand the biological underpinnings of memory and learning, scientists have used various neuroimaging modalities like EEG, PET, magnetoencephalography (MEG), and fMRI techniques over the past three decades. Among all of these, EEG and fMRI are much popular for some of their inherent benefits. Most of the existing literatures utilize fMRI and EEG responses to explore the processes involved in memory encoding, retention and recall, and signal transduction from one form of memory to the other during memory encoding and recall. The experiments were undertaken using different brain mapping techniques and memory tests. A review of EEG research studies on memory and learning are presented here.

1.9.1 Association of EEG α and θ Band with Memory Performances

Klimesch in late 1990s [42] indicates that "Phasic" or event-related changes in α and θ band power are related to memory performances. This study stresses upon "Tonic" or "baseline" power in relation to memory performance. Tonic changes in EEG power take place in response to the cardiac rhythms, fatigue, distress, neurological distress, and the like. It is also noticed that tonic changes are also influenced by aging of people. In contrast to tonic changes, phasic or event-related changes reflect processes, which are more or less under volitional control and occur at a rapid rate. *Phasic changes* are the event-related changes that can be measured for a particular task with respect to a reference interval like eyes closed and eyes open in the resting condition. *Tonic changes* are measured for a memory task (MT) with respect to another task (here, Klimesch has considered backward calculation in steps of 3 and 7 from 700). The memory task (MT) given to the subjects in this study is to remember 60 words, which are presented acoustically with an inter-stimulus interval of four seconds. After one minute of retention interval, a free recall task is performed. In this memory task (MT), the good memory, denoted by M+, and bad memory, denoted by M−, are distinguished with respect to the number of words one can recall.

To understand the tonic changes of memory, a backward calculation task (CT) was given to the subject while performing the memory task. Two difficulty levels of calculation task are carried out: easy and difficult. In easy calculation task, subjects are asked to close their eyes and subtract in steps of 3 from 300 (presented acoustically). On the other hand, in difficult calculation task, they are asked to subtract in steps of 7 from 700 in eye-closed condition. The subjects are instructed to avoid errors during calculation to whatever extent possible and to repeat calculations from the last step once an error is committed. An interval of four minutes is allowed for each subject to evaluate his/her performance. At the end of this interval, the subjects are asked to report the number they arrived at. As introduced before, Klimesch enumerated memory performance using two quantifiers, called good (M+) and bad (M−) performances. These quantifiers are assessed with respect to the count of the steps undertaken by individual subjects in easy and difficult calculation tasks. A threshold for good and bad memory performers was obtained by taking the median of the step counts obtained from all the subjects for two different tasks. The performance is declared bad, if the score (step count) goes below the median, and good, if it is above the median.

Statistical analysis is performed by computing Pearson correlation coefficient between the calculation scores for individual memory recall and the individual normalized power for each 0.25 Hz interval within the frequency window of 5–15 Hz. Differences in normalized power between the groups of *good and bad memory performers* and *good and bad calculation performers* are evaluated on the basis of *t*-tests. Comparison between good and bad performers reveals that good performers have a general tendency to exhibit a larger power than bad performers. The other comparative analysis is carried out between memory and calculation performance. It is interesting to mention that consistently large power estimates are experimentally observed within the upper α and β for memory performance analysis, while relatively lower power estimates are noticed for the calculation performance. Unlike memory performance, in calculation performance, good performers show more power in the lower α-band. In terms of correlation coefficient, positive correlations are found solely within a rather narrow frequency range of upper α (10.5–12.5 Hz) for memory performance. For calculation performance, positive correlations are found in lower frequency ranges (θ, lower α and β), but not in upper α band. Finally, tonic and phasic changes of memory are differentiated following the observation: large decrease in θ power and large increase in α power for good memory performances in tonic change as well as large increase in θ power and large decrease in α power for good memory performances in the phasic change.

Klimesch et al. [42] and Miller [43] following their independent research arrived at the same conclusion that α and θ power oscillations have a strong correlation with memory activity. From the existing works on EEG analysis of memory performance, he arrives at the following conclusions:

(i) If power spectra are calculated separately for a resting period (considered as baseline) and actual memory task performance (memorizing words or the like), a decrease in α power is noticed for the latter case. The frequency, at which the power spectra of baseline and that of memory task activities cross each other, is called *transient frequency* (TF), as shown in Figure 1.6. According to [44–46], there is an inter-subjective variation of the TF values, which range from 4 to 7 Hz.

(ii) α frequency band is the dominant frequency band in the human scalp EEG of adult persons, whereas θ frequency band is the dominant one in the hippocampus of lower mammals while performing memory activities [43]. In lower mammals, the θ frequency band ranges from 3 to 12 Hz [47] and for human it is 4–7.5 Hz.

(iii) θ power synchronization and α power desynchronization are associated with increasing cognitive load or WM load of human subjects [48–55] as shown in Figure 1.6.

(iv) Primarily an α power desynchronization is observed during eye-close condition of human subject, which demonstrates the association of α power suppression with the focused attention (FA) and semantic memory performance.

(v) The authors of literature [56–58] find that there is a strong correlation between α power and reaction time (RT) of individual subjects for any

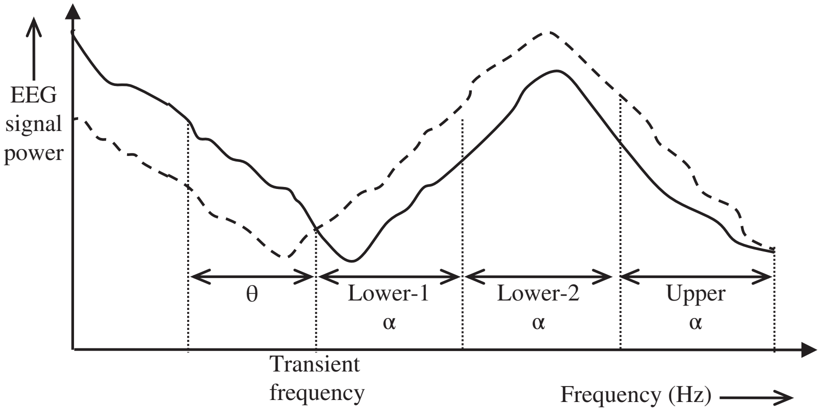

Figure 1.6 Transient frequency between θ and α frequency band.

memory tasks. The faster is the RT, the higher is the α band power. Similarly, subjects with slow memory performance show lower α band power.

(vi) Semantic memory and episodic memory performances can be discriminated based on the following observation of EEG band power changes. Upper α power decreases for the former one, whereas an increase in θ power is observed for the latter case.

(vii) Along with the episodic memory performance, increase in θ power is also associated with encoding of new information.

There exist other evidences of θ synchronization during memory encoding in [59, 60], where the authors S. Weiss et al. aim at finding functional and topographical differences between processing of remembered and forgotten nouns by the subjects. Participants have to memorize the nouns, presented to them by an audio cue. After the presentation of each list of 25 nouns, they are asked to recall the words previously encoded. The EEG signals, acquired during memory encoding, are then subdivided into two different epochs of subsequently recalled and of not recalled nouns. The first one-second EEG epochs of stimulus onset are Fourier-transformed and then the average power spectra for all 19 electrode positions and cross-power spectra between all possible electrode pairs of individual subject are computed. Finally, ground mean values are obtained by averaging the coherence values across subjects.

Repeated-measures ANOVA are performed on Fisher-Z-transformed coherence values for the θ frequency band. Significantly higher mean coherence in the θ band is observed during memory encoding of recalled than that of forgotten nouns independent of noun category (abstract and concrete). In order to obtain topographic information about single coherence differences between either recalled or forgotten nouns, the authors apply paired Wilcoxon tests separately for abstract and concrete nouns. Results are converted to error probabilities and presented as lines between the electrodes in schematic drawings of the brain. Generally, as revealed by ANOVA, recalled nouns elicit higher coherence than forgotten ones as well for concrete and abstract nouns. An increased coherence is observed for recalled nouns in frontal region and tempero-occipital regions within the left hemisphere. Concrete nouns have shown higher short-range coherence, whereas abstract nouns are correlated with higher long-range coherence.

1.9.2 Oscillatory β and γ Frequency Band Activation in STM Performance

There are evidences of oscillatory γ and β band activation with rehearsal of visual stimulus in the STM [61–65]. A second study [66], undertaken by Tallon-Baudry et al. makes an attempt to examine the role of sustained and transient memory activities on the γ and β band oscillations. Sustained activities refer to remnant information in the memory with/without continuous online rehearsal process. Transient activities, on the other hand, refer to the decaying memory states after a given memory cue is submitted to the subject, before to rehearse the information for memory restoration. A visual delayed matching-to-sample task is carried out to perform the experiment, where a participant has to identify two matched object shapes (deformed) presented to the subject with varying delay (800, 1200, and 1600 ms) condition. Varying delay conditions for same delayed matching-to-sample task helps discriminating the sustained and transient activities. Like the previous experiments, here also oscillatory γ and β rhythms are observed during the delay. The only observation that discriminate the sustained and transient activity is that occipital γ and frontal β activities slowly decrease with the increasing delay duration, while the performances of the subjects decrease in parallel, thereby concluding that occipital γ and frontal β activations are associated with sustained activities.

1.9.3 Change in EEG Band Power with Changing Working Memory Load

Wilson et al. [67] propose an interesting work to examine the topographic changes in brain electrical activities during varied memory workload. They consider memory tasks of different levels of complexity. The complexity is detrimental to number of memorization tasks assigned to the individuals. In their original work, memory tasks of four different complexity/difficulty levels are examined. A level 1 memory task refers to remembering one digit. Level 2, 3, 4, and 5 tasks, respectively, have to remember three, five, seven, and eight digits. Wilson et al. also consider three distinct protocols to study the memory performance. According to them, the protocols undertaken include (i) weighted condition, (ii) random condition, and (iii) blocked condition. In the weighted condition, 60% of the tasks presented to the subject have the easiest difficulty level (one digit), and 40% have difficulty levels between 2 and 5, distributed evenly across trials. In the random condition, the levels are evenly distributed across trials and also presented randomly to the subjects. In the blocked condition, the levels are evenly distributed across trials, but each memory test is presented with five blocks according to increased difficulty levels: 1–5, but any block of specific difficulty level may be replaced by "other item" instead of digits. Here the phrase "*other items*" refer to words or phrase, rather than digits.

To test the memory performance, EEG signals are acquired during the early retention phase, typically within the first four seconds counted from the offset of the memory cues, as this is the most active time-phase of memory retention. Next, to analyze the frequency domain information fast Fourier transform (FFT) of the time-domain EEG signals is computed at an interval of one second. Mean FFT is calculated over all subjects' EEG data, difficulty level, and EEG electrode regions. Statistical analysis is performed using ANOVA. Experimentally it is found that α band power decreases with increased cognitive demands or workload irrespective of the presentation context. The more α desynchronization is observed in the posterior left hemisphere regions for all the three conditions. During weighted condition, an increased θ activity is noticed over frontal region and to a lesser extent over left parietal and temporal regions and bilateral occipital region.

There exist extensive literature reporting possible functional relationship between the WM load and the spectral power density within the θ band of the acquired EEG signals. It is further reported [68, 69] that θ power increases linearly over parieto-central regions with increasing complexity of visual stimulus (as well as the WM load). Grunwald et al. [70] in their work makes an attempt to investigate the behavior of θ power during the processing of different complex haptic stimuli using a delayed recall design. To perform the experiment, the subjects are instructed to palpate 12 sunken reliefs with closed eyes. Ten seconds after the end of each haptic exploration, the subject has to reproduce the relief by drawing. After successful exploration, mean θ power of the acquired EEG signal and mean exploration time were calculated and analyzed using a linear regression model. A linear relationship between the exploration time and mean θ power is obtained over the fronto-central regions directly before the recall of the relief. Thus the study concludes that fronto-central θ activity correlates with the WM load independent of stimulus modality (visual or audio or any other).

Charbonnier et al. [71] in 2016 enunciated a new technique for WM load estimation by EEG-induced functional connectivity analysis of brain regions. A list of sequential digits is presented to the subjects during the memory encoding phase. During the memory recall phase, a probe item is displayed on the screen, and the subject has to recognize whether the probe item was present in the list of sequential numbers. The WM load is here considered at two distinct levels: two-digit memorization (low WM load) and six-digit memorization (high WM load). To undertake the preceding experiments, the following steps are undertaken. First, the EEG signal acquired is passed through a Butterworth-type band-pass filter (BPF). Next, the filtered signals acquired from four different region of interest (ROI), left frontal, right frontal, left parietal, and right parietal, are averaged region-wise to obtain an average response from real ROI. Charbonnier et al. proposed two alternative methods for classification of WM load into two classes: low and high. The first method, referred to as *pattern-based technique*, computes the cross-correlation between pairs of electrodes to obtain brain-connectivity measure. The second method, called *vector-based technique*, computes the mean or maximum signal amplitudes of each ROI. Then the mean values of different trials are utilized to form a feature-vector of individual class, which are subsequently fed to form a Fisher's linear discriminant analysis (FLDA) classifier. The classifier accuracy is used as the performance metric of WM load classification. Four connectivity measures, including cross-correlation, covariance, coherence, and phase-locking value (PLV) [72] are taken into account to compare the relative performance of the two proposed classifiers. After several experiments and performance analysis, Charbonnier et al. arrived at the conclusion that covariance analysis yields the best connectivity measure in the β band. In other words, the covariance-based results yield maximum classification accuracy for both the classification algorithms undertaken.

Another relevant study [73] on online cognitive load assessment for blind persons with various degree of sight-loss was undertaken by Saitis et al. in 2018. They selected unfamiliar indoor and outdoor charted routes to undertake the experiments. To select the right route, here the subjects have to face variety of indoor and outdoor mobility changes. The EMOTIV EEG headset is employed to acquire EEG signals from the subjects, and a measure, called percentage ERD/ERS (event-related desynchronization/event-related synchronization), is evaluated for six distinct frequency bands: δ, θ, lower α, upper α, β, and γ. To examine the difference in mental activity between the indoor and the outdoor scenes of varying complexity and obstacles in relation to the degree of vision-loss, a regression-like analysis is performed for the lower α and upper α bands, supported by the coincidence of degree of cognitive load with α-band power. A statistical analysis undertaken using *post-hoc paired sample t-tests* reveals that ERD/ERS in lower and upper α bands is significantly higher for almost blind than for severely impaired individuals in outdoor environment, whereas lower α synchronization is found higher for almost blind than the severely impaired ones in walk up/down stairs in the indoor environment. Finally, ERD/ERS of cognitive load is averaged over all electrodes per frequency band per second and fed to a classifier to classify low, medium, and high cognitive loads.

1.9.4 Effects of Electromagnetic Field on the EEG Response of Working Memory

There exist a few studies [74–76] examining the effect of electromagnetic fields (EMF) emitted by cellular phones on WM of a subject. In [74], C.M. Krause et al. examine the effect of cellular phone EMF on EEG responses during a visual *n*-back WM task. They observe a significant variation in the ERD/ERS. The experimental paradigm allows to examine several factors: (i) time (1500 ms pre- and post-stimulus), (ii) EMF off and on, (iii) targeted and non-targeted visual stimulus, (iv) WM load for 0, 1, and 2 back tasks, (v) left hemisphere and right hemisphere (RH), and (vi) ERD/ERS of 4–6, 6–8, 8–10, and 10–12 Hz frequency bands.

EEG signals acquired during the *n*-back task are at first band pass filtered with linear finite impulse response (FIR) filter in the four frequency bands: 4–6, 6–8, 8–10, and 10–12 Hz. The filtered EEG signal sample values are then squared to obtain the power values. The EOG electrodes are used for artifact detection and samples exceeding 100 μV are rejected. To examine the time factor, EEG signals are acquired for different time-windows: 1500 ms pre-stimulus presentation, 1500 ms during-stimulus presentation, and 1500 ms post-stimulus presentation. The mean power of reference interval is assigned to 0% from the relative power decrease (ERD) or increase (ERS) for baseline correction and is calculated separately for (i) target and non-targets and (ii) three WM load conditions: 0, 1, and 2. EEG data over each frequency band are averaged over left and right hemisphere electrodes for statistical analysis. All the previously mentioned experiments arrived at the following interesting results:

(i) The existence of EMF modulates the ERD/ERS responses only in the lower frequency bands of 6–10 Hz.
(ii) RT is not significantly affected by the EMF, rather it depends only on the task difficulty. With increasing memory load, RT increases.
(iii) Difference between the ERD/ERS responses of left and right hemispheres for targeted and non-targeted experiment are smaller while EMF is on than when the EMF is off at 6–8 Hz.
(iv) In 0- and 1- back task, an increase in ERD of both hemispheres is observed during target stimulus within the frequency band 8–10 Hz with EMF on. In contrast, the early ERS (~100–300 ms after stimulus onset) of both hemispheres is enhanced during non-target stimulus presentation in 2-back task within the same frequency band with EMF on.
(v) There is “no” significant change in ERD/ERS with 4–6 and 10–12 Hz frequency band when EMF is on.

There is a similar work by C.M. Krause et al. [75], who examine the effects of WM load only (without the effect of EMF) on the ERD/ERS components of EEG signals. They observe a long-lasting synchronization in 4–6 Hz lower θ frequency band in the frontal region, especially after the presentation of targets for all the 0–2 back tasks. Frontal ERS is also observed in 6–8 and 8–10 Hz, with highest synchronization in 2-back task and greatest ERD is observed in 10–12 Hz in the 2-back task. Therefore, 6–8 and 8–10 Hz ERS in the frontal cortex for the highest WM load reflect that attentional capabilities are most probably exceeded. This might reflect an inhibition of such brain regions (here, frontal cortex) no longer involved in task completion when alternative strategies are needed and utilized. These more "cognitive" strategies are reflected as an increase in 10–12 Hz ERD.

1.9.5 EEG Analysis to Discriminate Focused Attention and WM Performance

Discrimination of FA and WM performance is an indispensable study in cognitive neuroscience. Several neurobiological evidences reveal that there exist discrepancies between the brain functionalities during the execution phase of the above two cognitive tasks. In 2018, Mohamed et al. [77] takes up an initiative to classify FA and WM performance based on the EEG responses of the subjects during their mental engagement in the above two cognitive tasks. The following steps are undertaken to discriminate the above two cognitive modalities. First, the EEG signals are acquired by EMOTIV EEG headset and pre-processed to eliminate high frequency artifacts using a low pass filter (LPF), with a cut-off frequency of 50 Hz. Next, the direct voltage offset, which is added to the signal during sampling, is removed using a first-order FIR filter with cut-off frequency of 0.16 Hz. The resulting signal thus is free from direct current (DC) component. The spikes in the signal that appear to have high amplitude, hereafter called outliers, are removed from the sample values. The EEG signals thus pre-processed are fed to a feature-extraction unit to obtain relevant time-domain features including (i) minimum of the peak-to-peak signal, (ii) maximum of the peak-to-peak signal, (iii) signal mean value, (iv) variance of the signal, (v) coefficient of variance, (vi) kurtosis, (vii) skewness, (viii) quartile, (ix) 50 quartile, (x) 75 quartile, (xi) Shapiro–Wilk test, and (xii) Hjorth mobility and complexity and also frequency domain features including (i) power spectral density (PSD) in θ, α, β, and γ frequency bands and (ii) normalized power, computed using (1.1):

$$\text{Normalized Power} = 10\log_{10}\left(\frac{\text{activity power}}{\text{baseline power}}\right) \tag{1.1}$$

Taking into account the previously mentioned features, Mohamed et al. obtained 280 dimensional feature vectors (for each subject) to solve the preceding classification problem. This high dimension feature vector is reduced using a predictive model-based feature selection technique. In this method, predictors are mapped to fit the target, and the coefficients of the transformed predictors are used for ranking the importance of them, where weak predictors tend to have small coefficients. In addition, a q-regularization term is added to a proposed loss function, $E(x, y)$, to be minimized, where x is the set of predictors and y is the target. The objective function to be minimized thus is given by $E(x, y) + \lambda||w||$, where $||.||$ denotes l_1 and $l_2$regularizations and w is the coefficient vector of the model. Statistical tests are carried out to differentiate FA and WM scores. The results show that none of FA and WM distribution follow normal distribution. Rather FA is positively skewed, while WM is negatively skewed.

1.9.6 EEG Power Changes in Memory Repetition Effect

Discriminating the phase-locked and non-phase-locked event-related EEG activity is an interesting research arena. *Phase-locked EEG activities* refer to the event-related potentials (ERPs) including evoked potentials as well as slow negative potential shifts. On the other hand, *non-phase-locked EEG activities* refer to event-locked oscillations of induced α or β band EEG activities. Burgess and Gruzelier [78] examine the memory-related changes (old/new memory) in the non-phase locked component of EEG signals rather than phase-locked ERPs. Prior to initiate the experiments, the authors undertake predictions of memory-related EEG power changes on the basis of Treves and Rolls's [79] theory. The theory explains that a repetition effect in both the θ and the α bands exist at tempero-parietal region. Moreover, according to Klimesch's theory [80], the repetition effect would be expected only on the upper α band and not in the lower α. Klimesch reports that the memory-related α changes were well-established prior to their current research. To examine the θ band power changes associated with memory-task, the authors interpret that θ oscillations in a memory task are related to the *rhythmic slow activity* (RSA) in the θ range [81] in the hippocampal region. With these early predictions, authors start their experiments where the participants are asked to perform recognition tasks for the two different types of visual stimuli: face and word. Forty such stimuli are presented in 90 trials, where the first 10 trials are all "new" stimuli, of which 5 are repeated later. For trials 11–90, a probability of 0.5 is fixed for each item to be "old." For baseline correction, a pre-stimulus fixation cross of 1280 ms duration is presented to the subject. The acquired EEG signals are examined for the three frequency bands: 4.9–7.9 Hz for θ, 7.9–10.4 Hz for lower α, and 10.4–12.9 Hz for upper α. Filtering of the raw EEG data is performed using BPFs with moderately steep roll-offs of 56 dB/octave. The filtered EEG signal sample values are then transformed to *current source density* (CSD) values using Sidman's method [82]. The main advantage of using CSD, instead of scalp EEG potentials, lies in the observation that CSD provides more accurate spatial localization as it is less sensitive to distant sources than electrical potentials. Nunez et al. in 1994 [83] has shown that scalp CSD is proportional to electrical potential on the cortical surface and the square of CSD is proportional to the power of the electrical signal. The CSD values of each participant are then converted to ERD values following the methods adapted by Pfurtscheller and Aranibar in 1977 [84], as outlined in the following text:

(i) Calculate the mean power in the EEG signal at time t, $P_{\text{mean}}(t)$, given by

$$P_{\text{mean}}(t) = \frac{\sum_{i=1}^{n} x_i^2(t)}{n} \tag{1.2}$$

where $x_i(t)$ is the CSD of EEG signal of i-th trial and n is the total number of trials.

(ii) To evaluate the phase-locked component of CSD, i.e. event-related current source density (ERCSD), the following computation is performed.

$$\text{ERCSD}(t) = \bar{x} = \frac{\sum_{i=1}^{n} x_i(t)}{n} \tag{1.3}$$

(iii) As the research aims at studying the power changes in EEG signal, excluding the event-related changes, the non-phase locked EEG power is calculated by

$$P_{\text{npl}} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n} \tag{1.4}$$

(iv) Determine the mean baseline power and name it P_{npl}(baseline).

(v) Finally, ERD is evaluated by

$$\text{ERD} = \frac{P_{\text{npl}} - P_{\text{np}}(\text{baseline})}{P_{\text{np}}(\text{baseline})} \times 100\% \tag{1.5}$$

where positive values of ERD specifies increase in band-power and vice versa.

(vi) Mean ERD values are then computed for each 125 ms duration, as follows:

$$\text{ERD}_{\text{mean}} = \frac{\sum_{i=t-60}^{t+60} \text{ERD}(i)}{n_j} \tag{1.6}$$

where n_j = number of samples $\pm$ 60 ms.

Statistical analysis is undertaken using ANOVA for the modalities: words vs. faces, new vs. old stimuli, and left vs. right tempero-parietal response. Experimental results confirm that there is a short-duration increase in θ power during the first 250 ms with a peak in the temporal region. It is interesting to note that for recognition of words (and not faces), the repetition effect is pronounced in the θ frequency band with greater synchronization for new words than the old ones in the mid-frontal region. In α frequency band, there is a lateralized repetition effect, which occurs from 750 ms. In upper α, the effect is lateralized with greater desynchronization in the tempero-parietal region on the left for words and on the right for faces. For lower α, the lateralization was reversed.

In a different study [85], Noh et al. try to discriminate the brain responses of old and new stimuli based on single-trial scalp EEG activity recorded during memory recall phase. The authors use two types of stimuli as source information: spatial information and color information of old and new items presented to the subject, where the way of stimuli presentation is depicted from that used in [86]. While performing the experiments, the subjects are asked to remember the items presented to them as well as their contextual source information, which include (i) the side of the screen (left or right), where the stimuli was there during encoding, (ii) color of the outlined box within which the item was appeared, etc. The confidence level about the old/new stimuli recognition during recall phase is also checked by asking whether they are sure about their answers. EEG signals are recorded from their parietal and frontal brain regions using a 128-channel Geodesic EEG Sensor Net and the acquired signals are then pre-processed to feed to a classifier. The pre-processed data are divided into five categories prior to the classification:

(i) Source correct (SC), correctly retrieved old items with correct source judgments.
(ii) Source incorrect (SI), correctly retrieved old items with incorrect source judgments.
(iii) Correct rejection (CR), correctly rejected new items on successful recognition of new items.
(iv) Miss (M), unable to remember old/new.
(v) FA, wrong assumption about old or new stimuli.

A binary linear discriminant analysis (LDA) classifier with an automatic shrinkage approach [87, 88] is used to classify the following classes: (i) SC and CR, (ii) SI and CR, and (iii) SC and SI. The probability outputs ($0 \leq p \leq 1$) of the classifiers are denoted by classifier scores. A nonparametric paired t-test [89] is conducted on the trial-by-trial classifier scores of the different retrieval/subjective rating conditions. The results show that it is possible to predict successfully identified old vs. new items based on single-trial scalp EEG activity recorded during recall process. The old/new effect is also reflected in the frontal N400 (FN400) signal. In addition, it is found that apart from familiarity measurement, N400 can also reveal that there are differences between correct and incorrect context memories only for spatial information recognition, but not for color. The data of SC and SI show highest classification accuracies for frontal electrodes in spatial information recognition task.

1.9.7 Correlation Between LTM Retrieval and EEG Features

During long-term retention process, the semantic memory stores the acquired information in the hippocampal region, which is the primary storage of LTM. There exist extensive research outcomes exploring the underlying neural mechanisms of storage of information in LTM using fMRI device. Due to poor spatial resolution of EEG device, it still remains unexplored whether the LTM response can be captured using EEG modality. S. Hanouneh et al. [90] have tried to fill the void. They have taken attempt to examine the degree of correlation of the LTM retrieval process with the EEG band power and functional connectivity. To undertake the experiments, they focused on envisaging the EEG band power changes for a given LTM retrieval task. The experiment is carried out into two phases: semantic LTM encoding phase and recall phase. During memory encoding phase, a subject is exposed to a 10-minute animated educational science-related video containing human anatomy and physiology. During memory recall phase, the same subject is asked to answer 20 MCQs related to the learning contents. EEG signals are collected using a 128-channel EEG cap during both the memory encoding and retrieval phases. Raw EEG data are band pass filtered using an infinite impulse response (IIR) filter with pass band 0.5–48 Hz and roll-off 12 dB/octave. Eye-blinking and muscle artifacts are detected and corrected using *Berg and Scherg model* [91] and *Surrogate model* [92] approach with BESA software. For further analysis, the authors extracted three most fundamental EEG features from the filtered signals. A brief description of the three extracted features is given as follows:

(i) **Power spectral analysis**: The following steps are adopted to compute the PSD of the signal.
   (a) FFT with 50% overlapping to compute power spectra.
   (b) Powers are calculated for δ, θ, α, lower β, upper β, and γ bands to investigate the correlation with semantic memory retrieval.
   (c) Relative power was then computed as

$$P_{\text{rel}} = \frac{\text{Power of each frequency band}}{\text{total absolute power in 0.5–48 Hz}} = \frac{P}{P_{\text{total}}} \tag{1.7}$$

(ii) **EEG amplitude asymmetry**: It is often found that the amplitude of the EEG signals acquired from homologous regions of left hemisphere (LH) and right hemisphere (RH) are different. Here, the difference in EEG signal amplitude is computed as a proportion to the difference in signal power. Thus, the asymmetry in EEG signal amplitude is evaluated by the following transformation:

$$\text{EEG amp.asymmetry} = \frac{\text{abs.power of one electrode of LH} - \text{abs.power of one electrode of RH}}{\text{abs.power of one electrode of LH} + \text{abs.power of one electrode of RH}} \tag{1.8}$$

As the authors consider eight electrodes in LH and eight in RH, therefore, total number of pairs in EEG amplitude asymmetry features in both hemispheres is $= {}^{8}C_{2} = 56$.

(iii) **EEG coherence and absolute phase delay**: EEG coherence and phase of only correct responses for all 171 intra-hemispheric and inter-hemispheric electrode pair combination are computed. The number of pairwise combination of electrodes is determined by

$$C(m, n) = \frac{m!}{n!(m-1)!} \tag{1.9}$$

where m = number of electrodes and $n = 2$.

Finally, the coherence for all electrode pair combination is defined as

$$\text{Coh}(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f) \cdot S_{yy}(f)} \tag{1.10}$$

where $|S_{xy}(f)|$ = cross-spectrum between signal $x(t)$ and $y(t)$, $S_{xx}(f)$ = auto-spectrum of signal $x(t)$, and S_{yy} = auto-spectrum of signal $y(t)$. For complex computation, the coherence is finally computed as

$$\text{Coh}(f) = \frac{r_{xy}^2 + j_{xy}^2}{S_{xx} \cdot S_{yy}} \tag{1.11}$$

where co-spectrum r is for real and quad-spectrum j is for imaginary. Then, the phase angle θ_{xy} between two different EEG electrodes is evaluated as

$$\theta_{xy} = \arctan \frac{q_{xy}}{j_{xy}} \text{ rad} \tag{1.12}$$

θ_{xy} is then converted to degree. The absolute phase delay in degrees is then computed as follows:

$$\text{Abs.Phase Delay} = \sqrt{\theta_{xy}} \tag{1.13}$$

The statistical analysis is done using bivariate correlation in SPSS software to test the significant correlations between the EEG features of semantic LTM recall process. Eyes-open EEG recordings were considered as *baseline signal*.

After performing all the experimental steps mentioned earlier, the authors noticed that δ and θ band EEG powers are negatively correlated with task performance at frontal region, while there is a positive α band correlation in frontal region and negative α band correlation in parietal and temporal regions. High β power is correlated with LTM recall. Negative δ correlation is found in fronto-parietal and fronto-central region, whereas positive γ correlation in all the lobes is found. Phase delay shows highest degree connectivity in δ and α bands at frontal region and is found negatively correlated with LTM recall. Thus it is evident from the experimental results that the production of lower EEG frequencies in frontal region and higher frequencies in widespread regions are associated with LTM recall.

1.9.8 Impact of Math Anxiety on WM Response: An EEG Study

Mathematical anxiety (MA) is a serious problem in school students, which in turn gives rise to mental stress and fear in daily academic performances. A few related studies reveal that MA is primarily associated with the damage in the WM [93–95]. Getting inspired by the existing researches, M.A. Klados et al. [96] have taken a keen interest in examining the cortical EEG activations of math anxious persons. The authors aim at differentiating people who are high math anxious (HMA) and low math anxious (LMA) from their EEG responses by functional connectivity analysis. Two parameters are used to measure the degree of math anxiousness (behavioral analysis). The first one is the correctness of the given answers by d'prione index [97], and second one is the RT. *n*-Back tasks with increasing difficulty levels (1, 2, and 3) are used to test the WM performance. The cortical activation in terms of *current density reconstruction* (CDR) is evaluated using sLORETA software. Three separate time-windows, centered at 200, 300, and 400 ms (i.e. T_1: 180–220 ms, T_2: 280–320 ms, and T_3: 380–420 ms), are chosen for CDR analysis. These three time-windows are selected on the basis of global field power (GFP) values of the grand average trials, which indicate a clear discrimination between the two math anxious groups: HMA and LMA, with strongest GFP activity in LMA group in all tasks as compared with HMA. Statistical analysis of the CDRs are performed with *statistical parametric mapping* 8 (SPM8) [98] and ANOVA-*based GLM-Flex model* [99]. To realize the functional connectivity between scalp EEG electrodes, the inversion kernels, extracted by sLORETA software, are multiplied with the EEG signals averages over trials. A weighted graph is then obtained for each electrode pair combination, where the weight of each electrode-pair combination is measured by *magnitude square coherence* (MSC) value in a specific frequency f, computed as follows:

$$\mathrm{MSC}_{xy}(f) = \frac{|\mathrm{PSD}_{xy}(f)|^2}{\mathrm{PSD}_{xx}(f)\cdot\mathrm{PSD}_{yy}(f)} \tag{1.14}$$

where PSD(f) of x and y and cross-PSD are obtained using Welch method in each of the six frequency bands: δ, θ, lower α, upper α, β, and γ.

The behavioral analysis reveals a suppression of WM performance in MA by showing high RT and high error rates of HMA. LMA shows significantly greater activation in brain area related to WM in frontal lobe with increased activity in the supra-marginal gyrus. On the other hand, HMA exhibit strong activation in brain regions included in the pain and negative emotion network like the ACC, SMA, insula, and PHG, indicating corrupted WM.

1.10 Memory Modeling by Computational Intelligence Techniques

Over the past three decades, considerable amount of research has been undertaken by various research teams to analyze and model memory in diverse forms. While philosophers aimed at explaining the memorization of processes from the behavioral perspectives, experimental psychologists designed interesting experiments to study the learning and memorization processes in an integrated approach. However, unfortunately there is hardly any computational model of memory, capable of interpreting brain functionality using the electrical characterization of the brain response to stimuli. This section proposes several models of memory, which are primarily inspired by the computational models of neuroscience.

A commonsense reasoning reveals that the central part of a memory model is "Learning." Apparently, there is a question that appears before us: what is learning? Most of the contemporary textbooks on learning and memory define learning as changes in the neural architecture by means of additional synaptic connections and/or chemical (semi-permanent/permanent) changes in the neurons that participate in a learning task [23, 100]. Treaties of neuroscience also echoed the previously mentioned possibilities of architectural changes in the neurons/neural interconnections. Contemporary researches on artificial neural network models [101, 102], on the other hand, attempt to mimic the biological functionality of neurons by artificial means. Four different mechanisms [103] of learning paradigms are widely being used to mimic the biological learning of neurons. The paradigms include (i) supervised, (ii) unsupervised, (iii) reinforcement, and (iv) competitive learning. In supervised learning [104], a set of labeled training instances are submitted as input to the learning system/neural networks, where the labels denote the class-information of the instances. A learning algorithm is employed to adapt the weights (interconnection strengths) of the artificial neurons with an aim to produce the target class from the input measurement points listed against each training instance. Unsupervised learning, on the other hand, refers to grouping of objects based on certain similarity in the attributes of the objects. Unsupervised learning is also referred to as clustering in the literature. Reinforcement learning refers to learning by the principle of reward and penalty. In reinforcement learning, an agent acts on the environment and receives a measure of reward/penalty (negative reward) based on the measure of the action on the environment with respect to the target objective. The measure of reward/penalty is successively used to strengthen or weaken the existing interconnections [105, 106]. The last form of learning, referred to as competitive learning, allows competition between existing knowledge and new instances that support/or contradict the existing knowledge. A special layer in the neural architecture is preserved to allow competition, and the winning knowledge is saved in the form of adaptation of weights in the subsequent layers of the neural network [103].

In recent times, researchers are taking active interest to enhance the learning potential of artificial neural networks by adding significantly large number of layers to extract knowledge from raw data. It is important to add that in conventional artificial neural networks, the pre-extracted features are submitted as input to a pre-trained network to determine the class of the data point. Fortunately, deep learning networks (DLNs) can autonomously extract features from raw experimental measurements at first few layers of the network and determine the class label of the submitted patterns at the later stages. Although several interesting deep learning algorithms have been reported over the last five years, only a few of these received popularity for their diverse characteristics. The most popular among these are convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) models. A few of the existing DLN approaches for memory performance analysis are discussed in the following text.

In late 2000, X. Sun et al. [107] propose a new approach to predict the memory performance from pre-stimulus subsequent memory effects (SMEs) using EEG signals acquired during a memory encoding and recall task performance. During memory encoding phase, the subject has to memorize a word, presented by an auditory means via headphones and she/he has to make a semantic judgment about the word. A warning signal is presented 1.5 seconds before the stimulus presentation to make the subject alert. The encoding phase is repeated for 25 words with a separation of five seconds rest period. During memory recall, a probe item is presented to them and asked them to remember whether it is in the previous audio, presented to the subject during memory encoding phase. The subjects' level of confidence is checked by a 5-numbered rating scale. The authors proposed a computational approach to predict the memory performance by integrating two main stages: feature extraction and classification. They propose a CNN [108] for EEG signal analysis and name it ConvEEGNN. The architecture of the proposed ConvEEGNN is described as follows:

(1) The input layer L_{in} of the proposed ConvEEGNN receives EEG data-matrix $\mathbf{X}$ as its input, where each row of the matrix $\mathbf{X}$ contains an EEG time-series signal

$\overrightarrow{x}_i = [x_{i,1}, x_{i,2}, \dots, x_{i,n}]$ of i-th channel, where n is the number of EEG samples and $i \,\varepsilon\, [1, m]$, given by

$$\mathbf{X} = \begin{bmatrix} \overrightarrow{x}_1 \\ \overrightarrow{x}_2 \\ \vdots \\ \overrightarrow{x}_m \end{bmatrix}$$

(2) The first hidden layer L_c behaves like a spatial filter, which convolves data in the spatial domain.
(3) The filtered data are then convolved and sub-sampled in the temporal domain in the second hidden layer L_{cs}.
(4) The third hidden layer works as a feature extractor, where the useful features are extracted from the previous stage.
(5) The output layer is a classifier, which produces two classes of remembered and forgotten events from the extracted features.

The network is trained with two main steps: (i) feed-forward and (ii) back-propagation. For feed-forward pass, the network produces the initial weights and provides resulting outputs. For back-propagation pass, the error between the resulting output and the desired output is used to update the weights in order to gradually reduce the error. To study the effect of pre-stimulus SME to the memory performance, pre-stimulus and during stimulus EEG data are separately feed to the proposed ConvEEGNN. The result indicates that the prediction for both the stimuli are very close and have similar relation with memory process.

There exists another literature [109] on cognitive analysis on WM load from EEG responses, where the classification of four cognitive load classes (labeled with 1–4) is performed using a deep RNN. Here, four memory sets are prepared as stimuli, where each set contains either of 4, 6, 8, and 10 characters. In each trial, a randomly chosen memory set is presented to the subject during memory encoding phase. The authors do a labeling of WM load: 1–4, depending on the task condition with, respectively, 4, 6, 8, and 10 characters. EEG signals, obtained during memory encoding and recall phases using 32 channels, are then divided into 9 epochs, each of duration 0.5 second. Mean PSD in θ, α, and β bands are calculated for each epoch. The sum of the absolute power values for each of the three bands associated with each electrode are then transformed into 2D images to preserve spatial structures. The scalp electrode locations from 3D space are also transformed into 2D frames. Then Clough–Tocher technique [75] is used to interpolate scattered power over scalp and to estimate intermediate electrode values over a 32 × 32 mesh. The previously mentioned procedure, when repeated for each of the three frequency bands, results into three topographical spatial maps. The spatial maps are then merged together to form color images with three channels and is presented as input to a CNN. In the two-stage hybrid classifier network, CNN is used in the first stage to handle the spatial and spectral variations of the input data, and LSTM is used in the later stage to learn the temporal variation present in the input data. Two models of LSTM are used in the second stage: (i) bidirectional long short-term memory (BiLSTM) and (ii) LSTM. Experimental results indicate that CNN + BiLSTM gives the highest classification accuracy (92.5%) for the present cognitive load classification problem.

However, the traditional DLNs are unable to interpret the cognitive aspects of learning and memory. By cognitive aspects, we refer to the functional involvement of the brain modules in the overall process of learning and memory-related tasks. The book aims at developing the cognitive aspects of memory and learning in the settings of DLNs. The most difficult part of cognitive learning is that it cannot be modeled in isolation, as the brain processes, such as perception and attention, are inter-linked with cognitive learning. One approach to handle the situation is to model individual brain functionality by layers of the DLN, and the interaction among the cognitive activities by a group of layers of a feed-forward neural network. The learning aspects can be synthesized by necessary feedback loops with provisions for weight adaptation based on certain measure of error estimates. The book takes into account multi-stage feed-forward neural network with provisions for tuning weights in the desired layers to imitate natural learning.

Usually, local activation of neurons is taken into account to determine the memory performance. The local activation analysis is an integrated approach to analyze the firing response multiple neurons. The firing of local neurons often is not synchronous, thus possibly leads to confusing conclusions. To address this problem, single neuron response analysis is suggestive, but difficult for practical limitations of electrode placements in deep cortical brain circuits. Because of the previously mentioned difficulty, researchers nowadays prefer local averaging of neurons' response. The sense of averaging of local neuron population often reminds us about "*fuzzy logic*," which allows grading of signals at different levels of abstractions, such as HIGH, LOW, and MODERATE, undertakes reasoning with graded membership functions and finally takes one form of weighted averaging, called defuzzification (fuzzy decoding [110], to infer the response as a real non-fuzzy quantity). Another important aspect of fuzzy logic that too favors averaging behavior is concurrent firing of multiple fuzzy rules, thereafter taking sum of the inferences produced by individual rule for the overall inference generation. As the sum is one form of scaled averaging, the overall inference has a tendency to maintain the contribution of all the inferences produced by the set of rules.

In order to utilize the averaging behavior of fuzzy logic with its power of approximate reasoning, fuzzy logic has been selected as a basic tool of deep neural learning for memory modeling. To maintain homogeneity of neural characterization in the layers, fuzzy logic-induced neurons (simply, fuzzy neurons) of same functional characteristics are employed in a given layer. Thus each layer of the fuzzy neural net can be tuned to describe specific brain functionality, and a sequence of such non-homogeneous layers of the network represents the desired cognitive process, the user wants to emulate.

Several extensions to basic fuzzy logic have been undertaken over a couple of decades to enhance its power of dealing with uncertainty and approximate reasoning. Among the extensions, type-2 fuzzy set has earned much publicity. Two variants of type-2 fuzzy sets are gaining importance in recent times. They are known as interval and general type-2 fuzzy sets. An interval type-2 fuzzy set (IT2FS) is generally represented by two type-1 membership functions, called upper membership function (UMF) and lower membership function (LMF), and the space between these two membership functions is called footprint of uncertainty (FOU). The FOU provides a measure of uncertainty in an IT2FS. A general type-2 fuzzy set (GT2FS) is represented by a three-axis system with the x-axis reserved for the linguistic variable x, the y-axis representing the primary membership function, while the z-axis denoting the secondary membership function, which is a function of two variables: x and primary membership of x. The inclusion of the secondary grade provides one additional level of certainty measure of the primary membership at given values of the linguistic variable. Traditionally, GT2FS has been used for reasoning under uncertainty. However, there is ample scope for learning in presence of noisy/uncertain data. Here lies the importance of GT2FS in the modeling of memory.

1.11 Scope of the Book

The human memory system comprises four different levels of memory: sensory registers (SRs), WM, STM, and the LTM. The SRs acquire information directly from the sense organs. For example, visual information acquired is temporarily saved in iconic registers, the audio information acquired are saved in echoic registers, and the like. Because of limited storage capacity of the SRs, the sensory information or part of it is transferred to the STM for few seconds. In case the user wants to save the information permanently, he/she needs to transfer it to the LTM for storage over days/months or even years. The information saved in the STM is shared with WM for planning and decision making. The WM, in general, may be compared with a cache memory, whereas the STM is comparable with RAM of a computer. Generally, the cache pre-fetches part of a big program from the RAM for execution by a user-defined mapping function. Here too, parts of the STM need to be transferred to the WM by certain mapping function of user's choice. Although it is not clearly known the functional form of such user-defined mapping, apparently the user transfers the necessary information from STM to the WM to arrive at certain decisions from the available information in the storage.

The book attempts to model human memory system from three different perspectives. First, it proposes a simplistic model of WM built with fuzzy Hebbian learning. It is indeed important to mention here that Hebbian learning stems from Dr. Hebb's classic work on signal transduction in neural pathways. Dr. Hebb postulated that the strength of the signaling pathways between a pair of neurons increases when at least one of these neurons firing strength increases. Although there is no formal evidence of Hebb's postulate, there is hardly any contradiction too to refute the postulate. Naturally, Hebbian learning is widely acclaimed as the local learning of neurons and particularly for memory [111]. In the present context, Hebbian learning is here employed to represent the mapping from STM to WM and reconstruction of the STM response from the WM response by an inverse relation. Although the forward and inverse relations can be designed by a variety of ways, we here prefer fuzzy relational approach for the following reasons. First and foremost, the memory models are generally non-deterministic, i.e. hardly any speculation in the WM response can be inferred, even if there exists similarity with the STM responses. This requires employing certain mechanism to enhance the flexibility of the model to handle the inherent non-determinism. Fuzzy logic has the freedom to model such non-determinism and thus would serve an interesting application in modeling the STM to WM mapping. In addition, the fuzzy relational system has provisions to compute the inverse relation, which usually is absent in traditional non-deterministic system modeling. The previously mentioned two characteristics of fuzzy logic support its choice in STM to WM connectivity modeling for the present application.

Traditionally, researchers predicted memory response from the behavioral analysis of the memory encoding and recall. The memory responses thus obtained are unable to give interpretation of the STM to WM connectivity and prediction of the STM response from the acquired WM response. The merit of the book lies in predicting model behavior by acquisition of the EEG signals from the dorsolateral region of the prefrontal lobe [112], representing the WM, and predicting the response of the STM located in the orbitofrontal region from the acquired brain signals. The fuzzy relational model has been employed to represent the forward brain-connectivity, and an inverse solution to the forward max–min composition model is proposed to predict the STM response from the WM response.

The second perspective of memory models introduced in the book is concerned with two-dimensional shape reconstruction from visually examined memorized instances. Several brain lobes participate in the reconstruction of memory-bound imageries of acquired objects with an ultimate aim to reproduce the object shape by hand-drawing. The brain lobes involved include iconic memory for storing information about visually examined object shape, WM to process the traces of the iconic response (for example, filling the voids in the iconic memory response), parietal lobe for making necessary plans to move our arm for hand-drawing about the object shape, and motor cortex for execution of the motor activity needed for drawing the recollect the object shape. Here the subject, in multiple trials attempts to remember the acquired object shape and reproduce it by hand-drawing. Naturally, the early trials would have less chance of successes to reproduce the object shape. It is noteworthy that subjects in gradual trials update their memory reconciliation process to reproduce the more accurate/perfect object-shapes.

The book addresses the previously mentioned four-stage modeling of the brain system with special emphasis to learning of the STM and WM using feedback signals representing two different forms of computational errors. The first error signal, representing error in the model, is estimated and used as a control signal to feedback to the WM to adapt itself in the orientation to reduce the error due to the computational model. This corrective error feedback is employed at the end of each learning epoch. In other words, subjects at the end of each learning epoch, reproduce the object shape from memory, and the model is adapted to reproduce the geometry of the object as produced by the subject in that learning epoch. Similar learning cycles are repeated until no further improvement in the reproduced object geometry is detected. The second error signal corresponds to the perfection in the learning with regard to actual object shape to adapt the model further at the iconic memory level to reduce the error committed by the iconic memory model.

Examining performance of the iconic memory–STM interaction in reconstruction of two-dimensional imageries of acquired objects is difficult, unless there are provisions for reproduction of the mental thoughts into realization. Here, the subjects are asked to draw the recollected object shape. So, naturally, several brain modules like parietal lobe and motor cortex are involved to enable the subject draw the object shape. Realization of the parietal lobe and motor cortex is undertaken here by general type-2 fuzzy relations for its advantage in approximate reasoning under uncertainty. The uncertainty here appears due to contamination of the EEG instances by noise due to parallel thoughts/undesirable brain activations. Several variants of general type-2 fuzzy reasoning are available in the literature [113–116]. The one proposed here is referred to as vertical slice-based fuzzy reasoning, and the details of this is given later in Chapter 3.

The third model proposed attempts to assess the subjective motor learning skill in driving from erroneous motor actions. A set of fuzzy production rules, describing the motor actions to be learnt by the subject for possible sequence of occurrence of the selected brain signals, is provided. Type-2 fuzzy reasoning algorithms are proposed to infer the degree of motor actions learnt by the subjects, when one or more rules are fired after getting instantiated by available observations, concerning error in motor actions. Two different algorithms of type-2 fuzzy reasoning are proposed. The first one, called interval type-2 fuzzy reasoning (IT2FR), provides a simple scheme for automated reasoning to infer the degree of motor actions learnt. IT2FR requires insignificantly small computational overhead and thus is useful for real-time applications like the present one. IT2FSs having limited information resources, such as the bunches of user-provided type-1 membership functions only, is unable to offer quality inference in contrast to the inferences generated by its classical counterpart, the GT2FSs. The GT2FS is equipped with secondary measure of the primary membership functions, thereby offering users the benefits of natural selection of primary membership function values based on their secondary measures. The secondary membership functions in GT2FS thus enhance one additional dimension of judgment in the process of automated inference generation. The inferences generated by GT2FS are later type-reduced and defuzzified (decoded) to obtain the degree of motor actions learnt in the scale (0–100).

The fourth model proposed in the book introduces a novel strategy of designing a two layered deep LSTM classifier network to classify the human memory response involved in the face recognition task by utilizing the ERPs. The first layer of the proposed deep LSTM network evaluates the spatial and local temporal correlations between the obtained samples of local EEG time-windows. The second layer of this network models the temporal correlations between the time-windows. An attention mechanism has been introduced in each layer of the proposed model to compute the contribution of each EEG time-window in face recognition task and the attention weights are optimized using differential evolution algorithm with an aim to maximize the overall classification accuracy.

The last model proposed in the book deals with cognitive load assessment in motor learning tasks associated with driving. Functional near-infrared spectroscopy (fNIRs) is employed to capture the brain activations during different motor activities, such as braking, acceleration, and steering control. The prefrontal hemodynamic response is recorded in response to certain stimuli, such as sudden appearance of a child in front of the car, presence of a bumper ahead of the car, and the like. The recorded fNIRs data is preprocessed to keep it from noise and a set of statistical features are extracted from the filtered fNIRs data. Here, three classes of cognitive loads in the motor learning tasks for driving learners are considered. The classes are LOW, MEDIUM, and HIGH cognitive load. The fuzzy attributes are used to ensure classification in presence of measurement noise. Type-2 fuzzy classifiers are proposed to classify the measured cognitive load into one of three classes. Experiments undertaken confirm that the proposed vertical slice-based general type-2 fuzzy classifier outperforms its competitors in the classification of cognitive load of driving learners.

The first model proposed on STM to WM brain connectivity during memory encoding and retrieving STM response from the WM response during memory recalls provides a simple way to test the signal transduction between STM and WM and vice versa and thus opens up immense application potentials in diagnostic and prognostic applications pertaining to malfunctioning in signal transduction pathways from STM to WM. The second model on visually induced two-dimensional object-shape reconstruction, consulting iconic memory and STM, has interesting application in diagnosis of the brain regions responsible for iconic memory and STM performance. The third model, concerning motor learning skill assessment, helps in determining the learning skill of fresh drivers (driving learners) from the acquired brain response of different lobes. The method suggested is useful to check whether the driving learner has enough confidence to be a practitioner. The fourth model using deep LSTM network for face recognition task has an exciting application in differentiating brain responses for familiar and unfamiliar face recognition. The last model proposed aims at measuring the cognitive load of the driving learner using the hemodynamic response of the brain. The proposed technique would find several applications in determining subjective tolerance level with varying cognitive load condition. This is useful to job assignment to fresh software engineers based on their psychological strength and power of understand a new problem. In a nutshell, the book provides five interesting and useful models of memory and learning.

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