Neural Encoding and Decoding in Brain-Machine Interfaces for Learning and Memory Applications

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Abstract: The Brain-Machine Interfaces (BMI) offer an engineering model to record and decode neural responses. This paper will discuss the issue of neural activity of memory manifestation in the circuits between hippocampal and cortical neurons; the computational decoding algorithms, which transform the population-level allocation of neurons into intelligible cognitive terminologies; and the uses of the algorithms in creating closed-loop BMI systems in restoring memory. Cognitive BMIs are neural state estimation with machine learning and adaptive stimulation paradigms to help improve or repair mnemonic functioning. Hippocampal prototest and temporally directed stimulation models depict some of the potentials of such systems. To gain a clearer insight into the potential offered by BMIs in the field of cognitive neurotechnology, the last part of the paper will discuss the numerous technical issues surrounding the creation of such systems (signal stability, model generalization, stimulation precision) and their effect on the field of ethics.

Keywords: Brain-machine interfaces; Neural encoding; Neural decoding; Hippocampal circuits; Closed-loop stimulation; Memory restoration

1 Introduction

The two major functions of the brain, which give us the ability to attain adaptive behaviors is the cognitive functions that entail learning and memory. Neuronal loops found in the hippocampus, medial temporal lobe, and the connected areas help in learning and memory. These circuits encode information in the form of a pattern of activity at the population level, and modify it by synaptic plasticity [1, 2]. A large number of neurological disorders like Alzheimer's disease, epileptic seizures, heart attacks, and brain trauma seriously hinder the work of these circuits and make significant disturbances in memory creation and retrieval. Thus, there is a high interest in the creation of new neurotechnological strategies that can communicate directly with the neural activity that is behind the formation of learning and memory impairment.

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Brain-machine interfaces (BMIs) are among the many new emerging neurotechnologies currently under investigation to create direct communication with neural populations to record, decode, and stimulate the brain. BMIs are therefore offering a technology platform through which cognitive functions could be studied and potentially improved [3]. Preliminary investigations conducted through the use of BMI were aimed at the recovery of the sensory-motor functions. Nevertheless, there have been emerging inventions in the BMI technology that have enabled researchers to expand the technologies to higher-order thinking processes. It has been proven that neural activity due to memory in hippocampal and cortical networks can be forecasted to relate to memory performance and/or inner cognitive condition [4, 5]. It has also been shown, through closed-loop stimulation studies, that specific stimulation recruiting memory-related circuits can improve/repair mnemonic function. To illustrate, Hampson et al. were able to show that a spatial-temporal stimulation of the hippocampal activity used in the context of multi-neuronal models of encoding led to a significant enhancement of the memory performance of people with impaired cognition [6]. Moreover, Berger et al. showed that a hippocampal prosthesis, which was designed on the basis of a non-linear neural encoding and decoding model, could restore memory processing that has been impaired in animal models [7].

The effective usage of cognitive BMIs is conditional on the proper modeling of neural encoding and decoding processes. There are memory representations found within the groups of neurons whose behavior is regulated by the mechanisms of synaptic plasticity and long-range network interactions [2, 8]. Summary Consequently, computational models that are capable of processing high-dimensional, noisy neural signals are needed to extract relevant information out of the activity of these neurons. The improvement in machine learning has significantly improved these decoding performances and made it possible to determine the cognitive variables and adaptive closed-loop control in real-time. It is based on these developments that cognitive neuroprostheses have been established [9, 10]. Recent research has shown that BMIs are not an instrument of neural observation, but a platform for exploring the neural process of learning and memory as well as altering it. Nevertheless, there are still major issues with the correct decoding of the population-level neural codes in the long term, with the ability to time-lock stimulation to endogenous memory processes, and to translate such systems into consistent clinical therapy [3, 10].

This paper discusses the neural signal representation of memory representations within hippocampal and cortical regions, as well as computational modeling and decoding of these signals, and brain-machine interface closed-loop systems make use of these decodings to restore and control cognition. The paper will first define simple concepts of BMIs and neural coding, examine fundamental mechanisms, give illustrative examples, and finally explain limitations of the current state of research and perspectives.

2 Neural Encoding and Decoding in Brain-Machine Interfaces

An average BMI system comprises three fundamental modules known as neural signal acquisition, the computational encoding and decoding models, and output or stimulation sections [3].

Acquisition of neural signals Neural signal acquisition is a recording of brain activity; computational models encode raw neural activity into behavioral or physiological variables; and output modules translate decoded activity into stimulation or device control into stimulation or device control.

Encoding Models of the Brain explains how the hippocampus and the cortex of the brain depict the sensory and internal states and episodic associations. Decoding Models, on the contrary, seek to learn what kind of information on sensory and internal states, along with episodic associations, the brain represented, and can do so by measuring multi-unit spiking activity, or local field potentials [4, 5]. Experimental and modeling studies have indicated that the spatially distributed activity of the hippocampus and cortex has adequate information that can be used to accurately recreate the recollection of a subject concerning the past, belongingness of an item to a category, and internal cognitive processes. Thus, estimating the cognitive state of a subject in real time gives the possibility to operate the adaptive closed-loop control [4]. Yet, as population signals in the brain are usually high-dimensional and non-linear, it may be computationally difficult to estimate the neural activity of memory. This has led to the introduction of machine learning as one of the most important ways to study cognitive BMI, which makes real-time complex prediction of cognitive variables more accurate and allows implementing adaptive closed-loop regulation [9, 10].

Cognitive neuroprosthetic systems have been developed due to the merging of encoding models, decoding algorithms, and stimulation protocols. Particularly, the studies of hippocampal prostheses and closed-loop stimulations have shown that the decoded neural activity can be utilized to both estimate the memory states as well as to create specific patterns of stimulation that improve or rehabilitate the mnemonic functionality [6, 7]. All in all, these works demonstrate that the concept of neural encoding and decoding can be completed into a technology-based intervention in the memory-related brain circuits.

3 BMIs as Mechanisms and Applications in Learning and Memory.

3.1 Neural Mechanisms of Learning and Memory

The process of learning and memory is a result of both the coordination within hippocampal-cortical networks and the adaptation of the synapses of the single connections. Information is encoded, consolidated, and accessed in the patterns of the unfortunate populations at the systems level by the distributed circuits. Synaptic plasticity at the cellular scale modulates the strength of connections as one responds to experience, which forms a biological basis of stable memory representations. Intensive studies have closely identified two forms of synaptic plasticity, which are long-term potentiation (LTP) and long-term depression (LTD), in the formation of memory in both hippocampal and the cortical circuit [11]. LTP consists of an enhancement in synaptic efficacy that is sustained, and LTD consists of a decrease in the synaptic efficacy that is sustained.

The hippocampus is seen to be of critical importance in recalling episodic memories because it facilitates fast encoding of items with contextually useful information. Past evidence, both lesion and lesion studies, and even evidence regarding patients who had suffered serious damage to the hippocampus including patient H. M., supported this notion, which purported the hippocampus to be a primary site for the encoding of new declarative memory [1]. These past studies established that patients that had sustained considerable harm to the hippocampus could not make new declarative memories, and thus implied that the hippocampus was an essential part of the memory encoding and the initial memory consolidation procedures. Memory in the hippocampus is learnt using the ensemble firing patterns, where a population of neurons fires in a group to encode experience into a single activity state of the whole population of neurons. These group firing patterns will enable the hippocampus to have the ability to unify information from several of the other senses into one representation of an episodic memory.

Major new developments have been made in synaptic strength, and it has been shown that oscillatory network processes have been instrumental in memory processing because they have been able to offer a mechanism of network coordination between the large groups of networked neurons that are operating various parts of the brain. The fact that a significant percentage of neuronal recording of the hippocampus during exploration and learning shows theta oscillations (4-8 Hz) implies that the theta oscillations might be the means by which the temporal coding of synaptic information is organized and the facilitation of synaptic plasticity is mediated through regulation of the timing of the spikes [2]. It has been demonstrated that timings of stimulation with respect to the theta oscillation phase may have an effect on synaptic outcomes in the form of LTP with stimulation at the peak of the oscillation and LTD with stimulation at the trough of the oscillation [12], indicating that oscillation timing may affect the plasticity of learning related synapses. These results illustrate that rhythmic neural interactions contribute immensely to the modulation of the circuit changes that have a memory basis.

The hippocampal replay is also another mechanism of memory consolidation that is achieved by the reactivation of the events that occurred previously and is affected by the reactivation of neural firing patterns during the resting time or sleep. Replay events are normally accompanied by steep wave ripple complexes (high-frequency oscillatory bursts that are manifested during non-REM sleep and quiet wakefulness) in the hippocampus [2]. It is believed that replay leads to better memory traces and an increase in the transfer of information between the hippocampus and neocortical storage networks, thereby aiding long term stability of memory representations [8]. These connections between the hippocampus and cortex are in line with systems consolidation models, which are considered to be the way the hippocampus quickly develops memory representations that are later consolidated by other long-term memory representations sustained within the cortex over long time scales [1].

In combination, the above mentioned mechanisms (synaptic plasticity, hippocampal ensemble coding, oscillatory coordination, and replay-driven consolidation) can express the role that neurobiology plays in the learning and memory process. Notably, all these mechanisms produce different neural features that may be used as decoding tools as well as stimulation vectors in cognitive BMI systems.

3.2 Computational Models for Memory Decoding and Closed-Loop BMI Control

Neural responses in the hippocampus and in the cortices are highly dimensional; they indicate forms of cognition, e.g., of encoding states in memory, of the attentive situation, and of retrieval processes. Most of these signals are, however, noisy and spread across a large number of neurons. Thus, such signals are very hard to interpret, and detection of the signals has progressively relied on machine learning methods, which can determine concealed processes of neural population action and project spatial-temporal designs onto behavioral results [10].

The simplicity and ease of use of linear models (linear regression, the Kalman filter) have traditionally been used to do decoding due to their effectiveness and ease of use. Nonlinear models are usually, however, necessary in memory-related decoding to record intricate neural dynamics [10]. Over the past few years, deep neural networks and sequential probabilistic models have proven to highly enhance the precision of cognitive and memory-related decoders on the basis of executing non-linear correlations between neural activity and cognitive variables [10]. The sequential autoencoders have existed as an example, which are used to infer low-dimensional latent dynamics from population recordings and hence give a method of acquiring robust single-trial decodings of dynamically changing neural states [9]. These latent representations constitute an important component of the computer system of homing in on internal processes of the mind, such as state-dependent transitions in memory.

Besides the concept of passive decoding, the other essential innovation in the sphere of neurotechnology is the creation of closed-loop BMI. In closed-loop BMIs, neural activity is constantly observed and used to decode any pertinent cognitive or behavioral state in real time, and adaptive stimulation or feedback is provided based on the decoded result. This kind of system is particularly of interest to the understanding of learning and memory because the neural stimulation has to be administered at specific times in comparison to the memory-related neural states and must be specific to context so as to possibly improve performance without interfering with endogenous processing. It has been shown that stimulation in connection with memory-related neural activity can produce significant cognitive impairment. As an illustration, Ezzyat et al. demonstrated that the use of closed-loop stimulation of the temporal cortex, which was elicited by neural biomarkers reflective of poor memory encoding, enhanced performance in recall and the functional network activity [13].

Memory prosthetic systems have also been developed through computational models, and these are able to emulate transformations that occur in the hippocampal circuits endogenously. The approach created by Berger et al. entailed a multi-input, multi-output nonlinear dynamical model of signal transformation between sub-regions of the hippocampus that was used to form the stimulation patterns made using the decoding upstream activity [7]. This line of paradigm model-guided stimulation was subsequently applied to human participants, who found enhanced performance on a memory task [6]. These studies demonstrate the way to apply highly elaborate encoding and decoding schemes to generate not only forecasts of cognitive responses but also to generate stimulation patterns that would fix a damaged memory processing.

In a nutshell, the application of computational decoding and closed-loop control is the fundamental principles that facilitate cognitive BMIs. The availability of neural state estimation through machine learning and the adaptive stimulation paradigm can be used to analyze memory-relevant neural dynamics and generate clinically significant therapies for cognitive impairments through a BMI system in modern times.

4 Issues and Future Projections

Despite some significant progress in creating valid clinical neurotechnologies to learn and remember through brain-machine interfaces (BMIs), there are a lot of challenges to achieve. The viability of neural recordings over time is one significant impediment of coming up with a credible system. The quality of the neural signal(s) captured by implanted electrodes tends to reduce substantially with time due to tissue response, electrode movement/shift or/and change in the manner neurons fire; which in turn can result in a loss of precision in decoding the information contained within the neural signals, and make it challenging to develop and install chronic cognitive BMI systems [3]. Since memory representations exist throughout the brain and are dynamically modified because of synaptic plasticity, the decoding models employed in the cognitive BMIs should be capable of adapting to the nonstationarity in the neural code and be reliable across a variety of cognitive states.

As well as the problem of signal stability and the fact that models based on it become less predictable, there is another problem that should be considered to make neural stimulation a more reliable tool in the creation of cognitive BMIs, namely, the precision and the safety of neural stimulation. Although many experiments have been conducted and have shown that neuron stimulation can improve the performance of memory it is the timing, location and the parameters of the stimulation that are used that can be utilized that have a great impact on neural stimulation. Poorly targeted stimulation can disrupt the endogenous oscillatory coordination that is viewed to be central to normal memory formation and/or disrupt natural encoding mechanisms which in turn may result in poor cognition rather than enhanced cognition [13]. Subsequently, the needs of closed-loop systems in the future ought to involve incorporating the biomarkers that will help to identify the ability to recognize the ideal temporal windows that optimally stimulate the neural system, and offer personalized strategies of stimulation due to the fact that the neural state of each individual is different.

Lastly, cognitive BMIs have both ethical and translational issues. To illustrate, cognitive BMIs are characterized by major concerns regarding the confidentiality of the neural information, unintended behavioral modification, and the limits between function restoration therapy and cognitive improvement. Moreover, creation of clinically viable memory prosthetics will also entail creation of scalable algorithms and minimum invasive permanent recording methods so as to reduce risks of surgery and expand the use of such technologies.

5 Conclusion

The Brain-Machine Interfaces (BMI) were first introduced to help with motor restoration; however, currently BMIs are utilized in finer cognitive processes. It has been demonstrated by neuroscience research that a network of neurons within the hippocampus and cortex forms memory and that this network experiences synaptic plasticity, oscillatory coordination, and consolidation via the mechanism of replay. The mechanisms that form memory helps to support a population-level signal measurable and decode-able computationally to be used by neurotechnology.

The developments of Machine Learning as well as Neural Decoding have given researchers composition of cognitive variable within wide volumes of neural information in the Internet and in-vitro, which enables researchers to approximate to memory-related states in real-time. The closed-loop systems that involve such a decoding model gives a possibility to create adaptive stimulation strategies that will be able to enhance or substitute impaired mnemonic functionality. The therapeutic potential of cognitive BMIs to neurological disorders related to memory loss has also been determined with the help of hippocampal prostheses and temporally-targeted stimulation studies.

Although several improvements have been realised on BMIs, there are still numerous setbacks in the factor of long-term stability of recordings, generalisation of decodes with time and how safe and accurate stimulation can be applied. To address these constraints, scientists will be required to come up with adaptive computational algorithms, enhance neural interface technology and come up with well thought-out closed-loop protocols. Finally, further interdisciplinary progress in neuroengineering and computational neuroscience indicates that BMIs can be a potentially useful clinical instrument.

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