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REVIEW

A network engineering perspective on probing and perturbing cognition with neurofeedback

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Network science and engineering provide a flexible and generalizable tool set to describe and manipulate complex systems characterized by heterogeneous interaction patterns among component parts. While classically applied to social systems, these tools have recently proven to be particularly useful in the study of the brain. In this review, we describe the nascent use of these tools to understand human cognition, and we discuss their utility in informing the meaningful and predictable perturbation of cognition in combination with the emerging capabilities of neurofeedback. To blend these disparate strands of research, we build on emerging conceptualizations of how the brain functions (as a complex network) and how we can develop and target interventions or modulations (as a form of network control). We close with an outline of current frontiers that bridge neurofeedback, connectomics, and network control theory to better understand human cognition.

Keywords: graph theory; network neuroscience; neurofeedback; cognition; control theory

The notion that engineering principles are critical for advancing the frontiers of modern neuroscience is not new. Indeed, the marriage of these two disciplines is now commonly known as neuro-engineering.¹ The purview of this discipline is particularly large, including the use of theoretical, computational, and experimental tools to reveal fundamental principles of neural structure and function across species.^{2–5} It also includes efforts to “engineer” the brain in reverse—creating technological systems that perform brain-like computation—and forward—altering brain structure and modulating brain function in a targeted and theoretically predictable manner.⁶ Such engineering approaches were recognized in 2013 as key tools for tackling the challenges of mapping the brain.⁷ In humans specifically, the discipline seeks to reveal the foundations of cognition.

A natural confluence of many of these lines of inquiry lies in brain–machine interfaces (BMIs),

which capitalize on emerging instruments for both hardware and software in sensing, signal processing, and machine learning.^{4,8,9} And within the class of all BMIs, one noninvasive tool that receives attention for its potential to inform our understanding of human cognition is neurofeedback.¹⁰ Experimental paradigms including neurofeedback begin with the subject receiving sensory or behavioral feedback that is based on the current state of his/her brain activity—as measured by imaging or electrophysiology—in real time.¹¹ The participant then attempts to modulate that activity signal, either increasing it or decreasing it, in response to prompts from the experimenter. With training, many participants are able to learn to modulate the activity in specific brain regions on command.

Historically, neurofeedback training has been developed to assist individuals in the use of BMIs to overcome disabilities, injuries, or mental illness.^{10,12–18} For example, if one could control the activity of the hand motor cortex using mental imagery, that signal could be used to control a robotic hand.⁴ Or, in the case of mental illness, if one could control a region of the brain whose function

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is altered by the illness, one might have meaningful relief from undesired symptoms.¹⁹ Yet, while clinical applications have remained paramount in the use of these tools over the last decade or more, recent evidence suggests that neurofeedback can in fact also be used to probe the fundamental principles of cognition that explain how the brain relates to behavior.^{20,21}

The promise of neurofeedback in revealing principles of cognition builds on the fact that—in essence—it is a *perturbative* approach. Unlike the lesion approaches that were ubiquitous in early studies of neuroanatomy,²² which led to the field of brain mapping,^{23–25} neurofeedback enables the investigator to modulate brain activity in a targeted manner by offering the participant a view into the activity of a small volume of neural tissue. As a tool, neurofeedback offers several advantages over stimulation-based perturbation techniques, such as transcranial magnetic stimulation—subjects can learn to modulate activity on demand without the need for external stimulation hardware, and these learning effects can be sustained over several days.²⁶ Interestingly, such perturbative approaches are in fact the bread and butter of mathematics and physics, where they are used to examine the general structure of the dynamic landscape surrounding a point (see, for example, Refs. 27 and 28). The major benefit of a perturbative approach is that it facilitates generalization of an observation, and by extension the construction of a mechanistic theory. This ability to probe both the canonical form and the broader landscape of a dynamical system has proven fundamentally important in developing mechanistic theories in theoretical physics.

In cognitive neuroscience, the potential to use a perturbative approach like neurofeedback becomes particularly interesting when viewed in light of the emerging field of connectomics.^{29–31} Because the brain is not simply a collection of independent units but is instead a complex network of interconnected elements,^{32,33} manipulating the activity in one area can have nontrivial effects on other areas—even far from the modulated source.³⁴ Far from the mysteries of quantum mechanics, this action at a distance is a direct consequence of the complex pattern of structural wiring that links brain areas.^{35–37} Given this complexity, it is natural to ask, “What distributed network of brain areas is affected when a participant modulates the activity in a single brain region? Can

participants learn to modulate two regions at once, or large groups of brain areas? What do the answers to these questions tell us about the distributed computations that support complex cognitive processes? How would we choose the target region for neurofeedback to elicit a specific change in a large-scale, distributed functional network?”

Answering these questions requires a paradigm shift in our conceptualization of how the brain functions (as a complex network) and how we develop and target interventions or modulations (network control). In this review, we begin by briefly summarizing the use of neurofeedback to probe cognition, and we discuss the insights that these studies have offered into higher level cognitive processes in humans. Next, we highlight both the challenges and potential inherent in acknowledging that altering the activation of a single region can have nontrivial effects throughout the network. To better understand these widespread effects, we briefly describe the principles of network science and the organizational structure currently known to characterize the human connectome. These data lead us into the question of how to perturb the human brain via neurofeedback to move the brain from an initial state to a predictable target state. We describe the utility of network control theory in offering a mathematical framework in which to ground such questions, and we offer an outline of current frontiers that bridge neurofeedback, connectomics, and network control theory to better understand human cognition.

Neurofeedback for cognition: a primer

Like many other quintessentially complex questions in science, understanding how brain function relates to cognition requires a principled empirical approach. Most current efforts implement “open-loop” forms of inquiry, in which an input stimulus is used to elicit a measurable response in neurophysiology or behavior. At their core, open-loop methods enable neuroscientists to map the effects of a behavioral perturbation on the observed neural dynamics and, conversely, to map the effects of a neural perturbation on the observed behavior. In the forward direction (perturbing stimuli), one might measure the difference in neural response between different degrees of fearful stimuli. In the reverse direction (perturbing neurophysiology), one might lesion a neural circuit and measure the change in emotional response to those same stimuli.

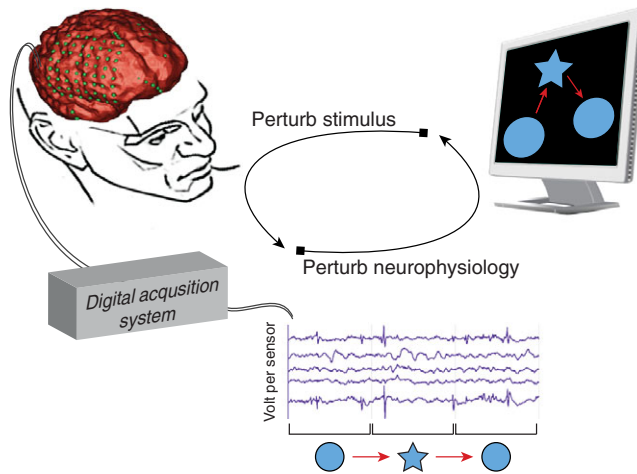


Figure 1. Open-loop perturbation of brain and behavior. Neuroscience has long exercised an open-loop approach to probe the characteristics of neural systems. By perturbing behavior and measuring change in neural dynamics or—in reverse—perturbing neural dynamics and measuring change in behavior, this method is used to generate a map between neural dynamics and behavior. For example, consider the following set of experiments investigating the neural basis behind the perception of shapes: to generate a forward mapping between stimulus and neural response, one might measure the change in neural activity of specific brain regions to visual perturbations of object shape; to generate a reverse mapping between neural response and stimulus, one might measure the change in perception of shape due to perturbation of neural activity (perhaps through lesioning or neurostimulation). The forward and reverse mapping are limited in their ability to describe how neural activity and behavior change together on a dynamical continuum. Neurofeedback enables investigators to close the loop around forward and reverse mapping approaches—in real time.

Together, the two types of open-loop experiments provide a forward mapping of behavior to neural dynamics and a reverse mapping of neural dynamics back to behavior. While these techniques offer particular utility in addressing open questions in cognitive neuroscience, they do not provide a means for addressing how function and behavior change concurrently, as a function of brain *state*. Indeed, to address this question, one must turn to “closed-loop” approaches (Fig. 1).

Closing the loop with neurofeedback

Neurofeedback enables closed-loop scientific inquiry by allowing the subject to *directly* perturb brain dynamics based on information about his/her current brain state or to *indirectly* perturb brain dynamics based on feedback about his/her current behavioral state. While both approaches enable the subject to modulate brain activity, they differentially test distinct aspects of cognition by affording flexibility in the design of the feedback signal,¹¹ which we address further below.

To test whether a subject’s ability to directly modulate target brain regions improves task performance, investigators can present sensory feedback that scales with the amplitude of brain activity.

The use of this technique has revealed that subjects can learn to regulate the activity of subcortical areas, including the amygdala^{38–40} and basal ganglia,⁴¹ and extended areas of the limbic system, including the insula^{20,42} and parahippocampus.⁴³ Interestingly, participants can also learn to modulate the primary sensory motor cortex (primary motor area,⁴⁴ premotor cortex,⁴⁵ and supplementary motor area^{43,46}) as well as higher-order areas, including the anterior cingulate cortex,^{20,42} ventral tegmental area,⁴⁷ frontal and parietal cognitive control areas,⁴⁸ anterior midcingulate cortex,^{43,46} and frontal cortex.^{43,46} Importantly, subjects who learned to successfully modulate regional activity demonstrated improved performance on a variety of cognitive tasks, including tasks eliciting cognitive processes critical for memory,^{39,48} mood,^{38,49} motor imagery,^{26,43–46,50} and perception of pain.⁴² Thus, neurofeedback affords flexibility in targeting distinct functional brain regions associated with different facets of cognition that include sensation, movement, emotion, attention, and learning.

While direct modulation of a neurophysiological signal is a natural place to start, one might also be interested in indirectly perturbing behavioral states and observing concurrent changes in brain activity.

Consider examining how the brain dynamically recruits different areas to perform easy versus difficult behavioral tasks—investigators can alter task complexity on the fly based on the amount of activity in the target brain region. To perform this real-time decoding and mapping of brain activation to behavior, neuroscientists have begun employing machine learning tools that link general linear models with multivariate pattern analysis.^{11,51,52} Briefly, a typical neurofeedback study utilizing these tools would implement the following general process: train a statistical model that discriminates patterns of brain activation in response to different stimuli, present the subject with a stimulus, ask the subject to perform a mental operation based on the stimulus, decode the altered pattern of brain activity using the statistical model, adjust the stimulus on the basis of the new brain state, and have the subject repeat the mental operation. The ability to perturb behavioral state based on underlying brain dynamics has immense utility in revealing functional mechanisms underlying changes in behavior.⁵³ Indeed, recent applications of this technique have yielded critical insights into the mechanisms of attention^{54,55} by altering task complexity during decoded states of attentional lapses.⁵⁶

Learning strategies in neurofeedback training

Exactly how participants learn to regulate regional activity in response to neurofeedback remains incompletely understood. To date, efforts have focused on two complementary strategies. In the first, the participant is provided with cognitive tasks that facilitate the activation of the target region, while in the second, the participant is simply provided with the feedback of regional activation and encouraged to identify his/her own strategy to modulate it. The two techniques have distinct advantages in the study of human cognition.

The earliest work in this field implemented the first approach by providing subjects with instructions to perform mental imagery by imagining the perceptual experience associated with the functional role of the target brain region.^{21,42,50} For example, to activate motor processing areas, one might picture oneself moving a limb, while to activate attention processing areas, one might concentrate on the given task. Evidence suggests that, when given such instructions, subjects display improved modulation of the target brain area within a day of training.²⁶

Put simply, learning to self-regulate brain activity is akin to learning any other skill.⁴¹ When given physiological feedback in addition to a recommended modulation strategy, evidence suggests that subjects display increased performance on related cognitive tasks in comparison to the scenario in which subjects are only given the modulation strategy.⁴²

Nonstrategic training of neurofeedback

Despite the apparent utility of a cognitive modulation strategy, it is also useful to understand to what degree subjects can volitionally modulate brain dynamics. Can subjects simply learn to modulate brain activity when given no pointers as to *how* to enhance the activity of the target region? Such a capability would be vital in modulating brain activity or connectivity in regions for which we cannot articulate a strategy. These possibilities open up a new realm of scientific investigation that could be particularly helpful in the study of neurological and psychiatric disorders with potentially discordant mappings of functional brain areas⁵⁷ or in tuning the temporal architecture of brain activity in healthy individuals.⁵⁸ Studies demonstrate that, even when explicit instructions or strategies are not provided, subjects can search for an effective strategy to self-regulate functional brain dynamics.^{26,38,47,57} Such open-ended experimentation is especially powerful for investigating how subjects employ unique strategies to modulate brain dynamics.^{38,40,57} Indeed, it is of interest to explicitly map individual variability in the chosen control strategy to the subjects' ability to modulate target brain areas. Understanding the relationship between cognitive strategy and effective modulation could inform experimental approaches to fine-tune the mapping between cognitive processes and functional brain regions (Fig. 2).

Probing cognitive abilities and disabilities

Broadly, direct and indirect neurofeedback are profoundly robust in their ability to modulate brain dynamics. Furthermore, they provide a systematic approach to query functional mechanisms of cognition that are often elusive in open-loop methods of investigation. By engineering the feedback signal, neurofeedback investigators can flexibly design novel experimental paradigms to study the role of cognition in single brain areas or across multiple brain areas in tandem. This practice has already demonstrated the ability to direct neurofeedback to more focal targets^{39,40,44,59–61} or to perturb

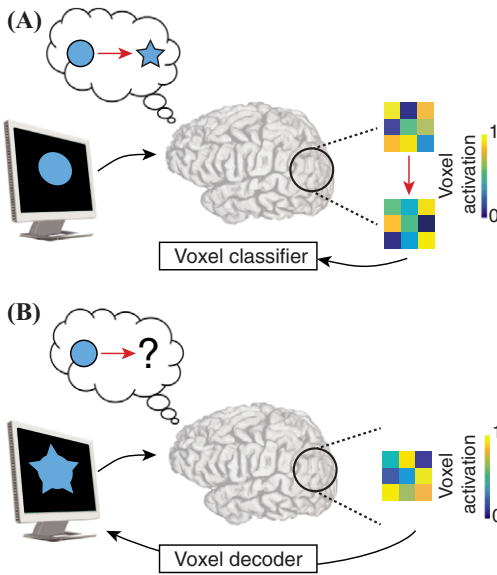


Figure 2. Probing cognitive state with neurofeedback. Indirect perturbation of behavioral state using neurofeedback is a powerful technique to probe the cognitive state space in individuals. Suppose that one wanted to learn the neural basis underlying spatial reasoning ability using a mental manipulation task. (A) The experimenter could present the subject with a circle and a star shape, and ask the subject to observe the stimuli and mentally imagine the circle morphing into a star. Meanwhile, a statistical model could be trained to capture the voxel activation pattern pertaining to the imagined shapes. (B) To probe and quantify the subject's thought process associated with mental manipulation, the experimenter might display the circle to the subject and ask the subject to use his or her mind to manipulate the object into a star. Using the shape-based model of voxel activation, the experiment could decode the mentally visualized shape from the voxel activation pattern—in real time—and feed the current state of the imagined shape back to the subject. By tracking how subjects explore the cognitive state space while learning how to perform mental operations during a task, investigators could map how individuals use different cognitive strategies to accomplish the task and could further map the distinct neural drivers of these strategies.

dynamics across more distributed targets.^{43,46,62} In addition, the difficulty of the neurofeedback training can be titrated to affect a specific change on both attentional circuits and regions devoted to internally directed cognition.⁶³ Particularly exciting applications to cognition include the revelation of associative learning in early visual areas,⁶⁴ visual perceptual learning induced by decoded functional magnetic resonance imaging (fMRI) neurofeedback,⁶⁵ and the sensitivity of these learning processes to the subject's state.^{66,67}

In addition to functioning as a probe for healthy human cognition, neurofeedback can also be used to identify and potentially treat cognitive disabilities. Particularly in populations with impaired mental health, neurofeedback enables the clinical study of mechanisms of dysfunction in neurologic and psychiatric disorders, and it also has the potential to provide noninvasive therapies to minimize the symptoms of such disorders.⁵³ Indeed, soon after its introduction in the late 1960s,^{12,13} neurofeedback was popularized in clinical contexts. Studies demonstrated its therapeutic potential in managing epilepsy,^{14,15} treating attention-deficit/hyperactivity disorder,^{16,18} and enhancing rehabilitation following stroke.¹⁷ Initially, these pioneering studies were limited to electroencephalography (EEG), but with more recent advances in other noninvasive imaging techniques, the tools have been translated to real-time fMRI.⁶⁸ Over the last few years, neurofeedback with real-time fMRI has been used to study schizophrenia,^{57,60} depression,³⁹ obesity,⁶¹ and addiction.^{62,69} While direct neurofeedback is used to improve patients' ability to self-regulate target brain areas and reduce clinical symptoms,⁷⁰ indirect neurofeedback is used to study functional dynamics underlying the different cognitive strategies used by healthy subjects and patients to modulate activity in dysfunctional brain regions.^{57,71} By using indirect neurofeedback to map cognitive differences between healthy subjects and patients, clinicians may be able to use behaviorally driven approaches to better diagnose individuals with disabilities and mental illness.

Advancing neurofeedback technology

Neurofeedback has yielded critical insights into cognitive function and dysfunction and is now ripe for innovation as neuroscience evolves toward understanding cognition in the broader context of brain networks.³³ Indeed, the emerging view of the brain as a network in the mathematical sense has been supported by a growing empirical ability to measure brain activity over a variety of spatial and temporal scales.^{30,32} Novel imaging technologies have continued to elucidate a hierarchical organization of the brain,^{72,73} ranging from the scale of individual neurons and neuronal populations to that of specialized large-scale functional areas.⁷⁴ Bridging the computational units at each scale are complex patterns of structural links facilitating the transmission and processing of information that support

cognition and behavior.²⁹ This hierarchical, multi-scale network architecture of the brain brings with it unique opportunities for the use of neurofeedback in understanding cognition.

Although prior work demonstrated that neurofeedback is effective in modulating dynamics of (1) individual neurons at submillimeter resolution and fast time scales,^{75,76} (2) millimeter-scale neuronal populations through oscillatory rhythms,⁵⁸ and (3) macroscale functional domains at slow time scales,^{59,68} modulating the way in which brain regions functionally interact is now becoming a tractable frontier. Using statistical models to measure functional connectivity and to construct an effective feedback signal for modulation, several studies demonstrated that subjects can directly perturb functional interactions between brain regions with fMRI-^{77–81} and EEG-based neurofeedback.^{82–84} Moreover, the feedback signal can be adapted to perturb the dynamics of individual connections^{80,81} or large groups of connections^{77–79} simultaneously.

While neurofeedback can perturb dynamics at different stages and spatial scales of functional processing, equally important is understanding how perturbations can have far-reaching impact on functional dynamics in non-targeted brain areas. Several studies identify changes in functional connectivity between the neurofeedback target and other brain regions.^{26,47,60,61,85–90} Other studies demonstrate changes in functional connectivity between pairs of regions completely outside of the area targeted by neurofeedback.^{26,85,87–89,91} Moreover, the observed changes in functional connectivity can be complex: upregulating or downregulating target brain regions may increase functional interactions between some brain regions and may decrease functional interactions between other brain regions.⁸⁷

Taken together, these findings underscore the potential complexity of the effect of neurofeedback on the brain. Yet, to date, little attention has been given to establishing a framework for predicting the impact of neurofeedback on broader network function. Building such a framework is critical for the improvement of feedback paradigms built to identify neurophysiological drivers of cognition and to treat neurological and psychiatric disorders while minimizing side effects. In the following section, we discuss the potential utility of network neuroscience in providing just such a framework.

Network neuroscience

At the confluence of neuroscience, engineering, and physics lies *network neuroscience*, a burgeoning field that offers a framework for describing brain circuitry at macro- and microscales.⁹² Drawing upon fundamental tools from graph theory,^{93,94} network scientists identify important features among elements of a system and measure similarity between these elements—based on these features—to synthesize models that describe an “ecosystem” of inter-related parts.^{95,96} These models can be probed and perturbed to understand how an individual element or a group of elements influences the system as a whole.^{97,98} This formalism can be used to study how elements of the brain (nodes) structurally or functionally link (edges) to one another and support behavior and cognition in health and disease.^{99,100} To construct brain graphs,³⁰ one can measure structural links between brain regions, such as those composed of macroscale white-matter fibers or microscale synaptic connections. Alternatively, one can measure functional links between brain regions, such as those estimated by similarity in brain dynamics. The pattern of edges between nodes can then be studied mathematically as a graph.^{30,32,33}

Mathematical underpinnings of network science

Formally, a graph \mathcal{G} consists of a set of N nodes \mathcal{V} and a set of $N \times (N - 1)$ edges \mathcal{E} .^{93,94} To tabulate the strength of edges between network nodes, one can construct an $N \times N$ adjacency matrix \mathbf{A} in which the entry at row i and column j refers to the weight of the edge between node i and node j . Multilayer networks extend the notion of a static graph to a higher-dimensional graph¹⁰¹—where nodes or edges change with condition or time, as in the case of dynamic functional brain networks^{101–106}—and are represented by an $N \times N \times T$ adjacency tensor with N nodes and T layers.¹⁰⁷ Using the adjacency matrix formulation, one can compute local, mesoscale, and global statistics to quantify the topological and topographical properties of brain graphs (Fig. 3). On the whole, these graph statistics can provide information about how neural information is represented, processed, and communicated between brain regions.

Local graph measures tell us about the nature of connections from a given node or between

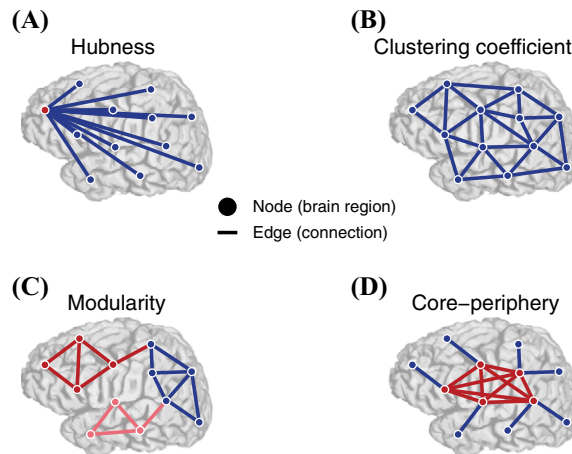


Figure 3. Multiscale topology in brain networks. Brain networks have unique organizing principles at local, meso-, and global scales that provide information about how neural information is represented, processed, and communicated between brain regions. Brain networks are modeled as a collection of nodes—representing regions of interest with presumably coherent functional responsibilities—and edges—structural connections or functional interactions between brain regions. (A) Node centrality describes the importance of individual nodes in terms of their connectivity relative to other nodes in the network. Nodes with more connections or stronger edges tend to be hubs (red), while nodes with fewer connections tend to be isolated (blue). (B) Clustering coefficient, a measure of connectivity between the neighbors of a node, is another local measure of network topology. Unlike network topologies with strong hubness qualities, as in (A), networks with strong clustering coefficient demonstrate a high density of triangles that is believed to facilitate local information processing. (C) Modularity is a mesoscale topological property that captures communities of nodes that are tightly connected to one another and weakly connected to nodes in other communities. Modular organization underlies a rich functional specialization within individual communities. Here, nodes of different communities are colored red, blue, or pink. (D) Networks with core–periphery structure exhibit a set of tightly connected nodes (core; red) sparsely connected to a set of isolated nodes (periphery; blue). This organization is in stark contrast to the modular organization in (C). The core–periphery architecture is a characteristic of networks that integrate information from isolated regions in a central area. Adapted with permission from Ref. 127.

neighbors of that node. One simple, yet important, local statistic of a node is *centrality*—how influential a node is in the context of the broader network.⁹⁵ Centrality can take many forms, such as *degree*, the number of edges connected to the node (Fig. 3A), or *betweenness*, the number of shortest paths between any two nodes that must cross the node in question. Degree centrality has been particularly useful in identifying hubs of neural processing that interact with many different brain regions.^{97,108,109} A second local statistic that is often used to describe brain graphs is the *clustering coefficient*—the fraction of a node’s neighbors that are also connected to one another¹¹⁰ (Fig. 3B). The clustering coefficient describes topological organization thought to underlie local processing of neural information.^{111,112}

At the mesoscale, one can quantify the tendency of brain regions to form *communities*—tightly connected groups of nodes that have more connections to one another than to other groups of nodes^{113,114}

(Fig. 3C). This modular architecture is thought to support the brain’s segregation into functionally specialized units.^{33,115,116} Brain graphs can also exhibit *core–periphery* structure, in which a densely interconnected group of core nodes is connected to a sparsely interconnected group of peripheral nodes^{117,118} (Fig. 3D). The core–periphery network structure has been studied for its role in explaining domain-general versus domain-specific processing of brain areas,¹¹⁹ in which specialized neural processing in peripheral regions is integrated by a strongly connected core to support higher-order cognition in learning^{104,120} and language.¹⁰⁶

Finally, global statistics provide a summary of network topology. For brain networks, the *characteristic path length*—average shortest path between all node pairs⁹⁵—is thought to measure how easily neural information can be transferred between brain regions. Brains with shorter path lengths are thought to transfer information more efficiently than brain networks with longer path lengths,¹²¹

thereby leading to greater intelligence.¹²² A similar, dynamical measure of information transfer that has been of recent interest is *synchronizability*—the ease with which dynamics at each node can synchronize based on the arrangement of edges.¹²³ Synchronizability has also been studied in the context of graph robustness and vulnerability to random and targeted attacks to nodes.¹²⁴ In brain networks, synchronizability is thought to be maintained between a critical boundary of order and disorder.¹²⁵

It is important to remember that each statistic is sensitive to network phenomena of a specific scale, and a comprehensive, multiscale quantification of brain network topology requires integration of the output of these measures.¹²⁰ For instance, local information processing at hub nodes might be projected broadly to mesoscale modules for function-specific processing that might require globally short path lengths to ultimately integrate and bind the information of each module.¹⁰⁰ This framework can be used to query how different elements across multiple scales of network architecture contribute to the processes underlying human cognition.¹²⁶

Cognitive network neuroscience

Graph theoretic approaches for understanding cognition have become increasingly popular over the past decade, largely due to their utility in describing the interregional relationships between neural processing units elicited by cognitively demanding tasks.¹⁰⁵ Application of graph theory to noninvasive brain imaging in humans has yielded critical insight into mechanisms of intelligence, linguistic processing, attention, decision making, learning, memory, and cognitive control.^{100,126} Pragmatically, it is useful to separate these insights into those produced by structural brain networks^{35,128} and those produced by functional brain networks.^{97,125}

First, structural brain networks constructed from diffusion-weighted imaging of white-matter fiber pathways^{35,36} describe the fundamental scaffolding upon which functional brain networks operate.¹¹⁵ Because of their potential role in constraining functional brain dynamics,^{129,130} structural brain networks are thought to play important roles in shaping our basic cognitive abilities—such as processing speed, working memory, motor skills, and task switching.¹²⁶ For example, longitudinal structural imaging has revealed localized changes in network microarchitecture associated with learning

new skills,^{131,132} and moreover that the strength of structural connections between task-relevant brain regions predicts individual differences in the rate at which those skills are learned.¹³³ The relevance of structural connectivity for cognition extends to clinical cohorts. For example, patients with anatomical disruptions caused by traumatic brain injury exhibit structural network changes—such as a lengthening of the shortest path length—that are associated with decreased performance on tasks that required switching and inhibition of cognitive resources.¹³⁴

While structural brain networks reveal important correlates of cognitive ability, a more nuanced dissection of cognitive processing also requires the use of functional imaging methods. Functional brain networks provide a glimpse into network *processes* (as opposed to structures) that support cognitive function. One recent study highlighted the importance of functional network topology for cognition by tracking longitudinal changes in the behavior of patients with traumatic brain injury; patients with lesions in brain regions that connected to several functional modules exhibited more widespread cognitive deficits compared with patients with lesions in network hubs.¹³⁵ Patients with traumatic injury also exhibit distributed increases in connectivity during the Stroop task—which requires switching of cognitive resources—that is associated with reduced performance on the task.¹³⁶ In healthy individuals, differences in global connectivity from specific cognitive control areas predict fluid intelligence.¹³⁷ Beyond the performance of a single task, evidence suggests that functional brain networks also reconfigure as individuals traverse different cognitive states¹²⁵ and that the flexibility of this reconfiguration can be used to predict learning in future training sessions.³⁶

Together, these studies underscore the role of network topology and network dynamics as fundamental mechanisms of cognition. Such insights lay the groundwork for exploring how neurofeedback can be used to perturb network properties and thereby more effectively probe drivers of cognition.

Linking neurofeedback to network neuroscience

In the preceding sections, we explored state-of-the-art capabilities in neurofeedback to perturb brain dynamics, and we introduced a robust framework in network neuroscience for studying the interactions

between brain dynamics and the structural networks from which these dynamics originate. Here, we begin to address how the thoughtful integration of neurofeedback and network neuroscience could enhance the study of cognition.

In principle, network neuroscience can be used to identify target brain regions for neurofeedback. Evidence suggests that neurofeedback is differentially effective in distinct brain areas.¹³⁸ While initial interpretations suggested that this differential effectiveness is due to the inherent differences in the types of cognitive processes that brain regions perform, a second possible explanation is that brain areas are differentially sensitive to neurofeedback based on their connectivity profile. It is intuitively plausible, for example, that regions of the brain that are densely functionally connected with one another (such as the default mode) will be easier to control as a collective—owing to the breadth of potential control mechanisms¹³⁹ and cognitive strategies—than regions of the brain that are sparsely functionally connected (such as the frontal pole). It will be interesting in the future to determine whether the connectivity profile of a region, or the complexity of the information it processes, is a better predictor of its response to neurofeedback.

Beyond informing our understanding of the impact of neurofeedback on specific brain areas, network neuroscience can also be used to predict the impact of targeted neurofeedback on other brain regions. For example, structural connectivity or resting-state functional connectivity could pinpoint network hubs, such as cognitive control areas,^{140–142} that interact with many other brain areas and serve as a potential target for modulating distributed brain dynamics with neurofeedback. Such a capability could be used to study self-regulating brain dynamics¹⁴³ in cognitive control regions and their effective control of other brain areas as humans switch between distinct tasks.¹⁴² A similar approach might be employed to investigate whether modulating brain regions that integrate functionally distinct network modules¹⁴² could help subjects better learn tasks that require cooperative or competitive interactions between separate cognitive domains¹⁴⁰—such as visuomotor interactions in novel skill acquisition.¹⁴⁴

More generally, our ability to connect network topology to cognition offers a critical opportunity to model and predict the effects of neurofeedback on

cognition. Simultaneously, advancements in neurofeedback can be used to investigate network drivers of cognition: by designing the appropriate feedback signal, neurofeedback can be engineered to modulate not only brain regions but also specific brain networks. This capability opens new doors to test the ability of subjects to modulate specific network properties: Could a subject be trained to modulate the flexibility of a functional module, the participation of a brain region in multiple modules, or even the characteristic path length of the global network? Our ability to modify the feedback signal to accommodate network statistics could have substantial impact on our understanding of how perturbation of network structure affects cognitive ability. Such a capability would also inform the design of novel intervention strategies for patients with neurological disorders or psychiatric disease characterized by disrupted patterns of functional connectivity.

Caveats and future directions

While the prospect of linking neurofeedback and network neuroscience is promising, it is also important to adopt a measured approach in which we acknowledge the pitfalls and limitations inherent in the techniques. First, a note on interpretability: network statistics quantify graph properties from the theoretical perspective of statistical mechanics and information processing, and thus they require a conceptual leap if connected to neurophysiologic phenomena.^{145,146} For instance, the relationship between connectivity derived from functional imaging and the amount that two brain regions are in fact *communicating*¹⁴⁷ remains undetermined. Or consider the shortest path between areas in a brain graph: Does the brain utilize shortest paths?¹³⁰ Or does it preferentially utilize longer paths or walks?^{37,133} Although novel technologies are needed to help bridge these areas of scientific understanding, we remain optimistic that network neuroscience will provide a dynamical systems-level characterization and understanding of behavioral and cognitive processes.

A second crucial caveat relates to the importance of distinguishing between correlation and causation. A substantial body of work now demonstrates that network measures can be good predictors of cognitive ability based on their degree of correlation to performance metrics. However, these predictions do not equate to *causation*. In fact, explicitly

identifying causation will require a coupling between neurofeedback and network-based approaches to the study of cognition: by modulating network topology with neurofeedback and evaluating the concurrent change in task performance, we can begin to understand causal effects of network architecture on cognition.

A third and very fundamental consideration relates to the question of whether neurofeedback can be truly targeted to a single region or whether it only ever activates a distributed network. In truth, knowing the degree to which a specific neurofeedback paradigm targets a single region versus many regions remains challenging, and this uncertainty is an important consideration for studies seeking to combine network approaches and neurofeedback training. For example, prior work demonstrates the ability of subjects to regulate brain activity in spatially confined brain regions.⁵⁹ Specifically, they show that, with training, activation was significantly increased within a predefined target area (somatomotor cortex) relative to the rest of the brain, an observation that suggests that spatial specificity may be achieved with neurofeedback. More recent work confirmed the hypothesis that functional connectivity from the target brain region (ventral tegmental area) to adjoining brain regions is directly caused by volitional activation of the target and not mediated by practice with or without false neurofeedback.⁴⁷ Thus, they reason that changes in network connectivity are due to the successful perturbation of the target and not associated with the task. This observation, however, still leaves open the question of whether increased functional connectivity occurred in successful perturbations during training or as a result of posttest perturbation. Other work has developed techniques to study the differential effects of perturbation during training and perturbation after training (transfer) on functional connectivity.⁸⁹ Comparing functional connections stemming from the neurofeedback target, they found more distributed changes during training and specific changes during transfer. These studies present evidence that (1) neurofeedback can activate spatially confined brain regions, (2) target activation and the resulting increase in functional connectivity can be directly related to successful neurofeedback, and (3) methodological innovations are capable of teasing apart changes in functional connectivity due to training perturbations versus transfer perturba-

tions. Nevertheless, it will be important in the future to understand the degree of targeting possible in any given neurofeedback training paradigm, as well as in any given subject, when considering informing such experiments with predictions from network science.

Perhaps most importantly, the possibility of revealing causal relationships between network architecture and cognition with neurofeedback also supports the potential to build computational models or theories of brain network function from first principles.^{148,149} Setting aside characterization and description, and even setting aside correlative approaches to link brain network function to observable behavioral variables, models and theories provide mechanistic understanding¹⁵⁰ and the ability to generalize inferences to unseen scenarios. What might such a model or theory look like? In the following section, we discuss the potential utility of network control theory in providing just such a model.

Network control theory: a tool to predict impact of modulation

Network control theory is a mathematical modeling framework that addresses the question of how energetic input to a node in a network affects the dynamics of the networked system.^{151,152} Stemming from early work in the 1970s on *structural controllability*,¹⁵³ the theory is built on two pillars: a model of the system's dynamics and an estimate of the system's network structure.¹⁵⁴ In contrast, graph theory stands on only one of these pillars (the network structure) and is devoid of the other (a model of system dynamics). These differences in the nature of the two theories directly affect how they can be used.^{142,155} graph theory provides descriptive statistics of a network's organization, while network control theory provides a prediction of how the change in energy at a node will alter the system's dynamics. While graph theory offers tools for characterization, network control theory posits a mechanism for system function.

Traditionally, network control theory stems from the older field of simply *control theory*, which has been used to inform the control of robotic, technological, and mechanical systems. The simple difference between control theory and network control theory is that network control theory deals with the application of control theory to systems characterized by complex interconnection patterns.^{151,152}

These patterns significantly affect the control strategies that a system can perform or respond to and further affect the energy required for certain control goals. In the realm of neuroscience, network control theory therefore differs from neural control engineering more generally¹⁵⁶ in its explicit treatment of brain network architecture.

A few relevant concepts and tools

In a brain, questions of control can be separated into two types: (1) how does the brain control its own dynamics and (2) how can brain dynamics be controlled via external intervention. When applied to the former question, network control theory can offer insights into cognitive control,¹⁵⁷ decision making, and other forms of executive function.^{142,158} When applied to the latter, network control theory can inform the use of neural modulation via neurofeedback or brain stimulation,^{34,159} the development of cognitive tasks for explicit tuning of brain dynamics, and the understanding of how sensory stimuli impact those dynamics.

To address both types of questions regarding internal and external control, one needs to begin by writing down the two pillars of the theory: a model of the system's dynamics and an estimate of the system's network structure. A simple first step is to use a discrete-time, time-invariant, noise-free model of system dynamics^{129,160} and a structural network estimated from diffusion imaging tractography in humans,³⁵ representing the white-matter pathways crisscrossing cortical and subcortical areas. Of course, these choices are accompanied by model assumptions and caveats associated with the empirical data, both of which need to be acknowledged. (See next section for an explicit treatment of these topics.) Nevertheless, they remain a useful starting point for the application of the theory to human neuroscience.

Within this framework, network control theory offers a few important concepts and tools. The first important concept is that of *controllability*, which indicates whether a system can be moved from a specified initial state to a specified final state with finite energy and in finite time.¹⁵¹ In initial applications of these algorithms to noninvasive structural neuroimaging data in humans, evidence suggests that the human brain is practically impossible to control from energy injected into a single brain region.¹⁴² This result motivates a more nuanced

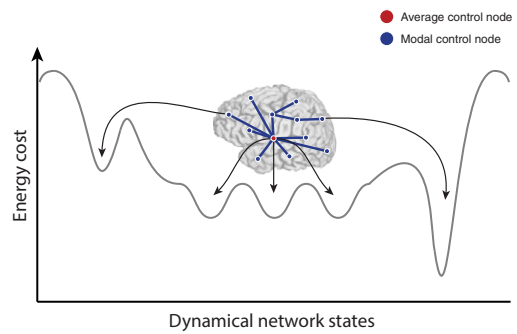


Figure 4. Brain network controllers drive transitions between dynamical states. To accomplish behavioral and cognitive goals, brain networks internally navigate a complex space of dynamical states. Stable brain states may lie in basins of local minimum energy—requiring the brain to expend metabolic energy to move over high-energy peaks when transitioning from the current state to the next state. Within the space of possible dynamical states, there are easily accessible states and harder-to-reach states; in some cases, the accessible states are healthy, while in other cases they may contribute to dysfunction, and similarly for the harder-to-reach states. Two commonly observed control strategies in complex systems are average control and modal control. In average control, highly central nodes navigate the brain toward easy-to-reach states. In contrast, modal control nodes tend to be isolated brain regions that navigate the brain toward hard-to-reach states that may require additional energy expenditure.¹⁴² Adapted with permission from Ref. 127.

assessment of whether there are particular control strategies that are possible for the brain and whether the system is controllable with a larger number of input sites.

In the engineering literature, common control strategies include (1) *average* controllability, which describes the ease with which the system can be moved to nearby states on the energy landscape; (2) *modal* controllability, which describes the ease with which the system can be moved to distant states on the energy landscape; and (3) *boundary* controllability, which describes the ease with which modules in the network can be coupled or decoupled.¹⁵² In applications to human diffusion imaging data, these concepts have proven useful in offering structural explanations for the areas that affect cognitive control^{142,158} and the impact of stimulation to the target brain region.³⁴ An even finer account of the brain's dynamics can be obtained by studying the exact transitions from one brain state to another, with assumptions on the need to minimize energy of transitions and minimize the distance that the brain traverses through state space to affect the transition¹⁵⁵ (Fig. 4). Applications of these

algorithms to human diffusion imaging data have offered an explanation for the anatomical structure of the brain's default mode network¹⁵⁵ and a prediction of which regions in the network are most likely to assist in a given state transition.^{155,161}

Limitations, caveats, and extensions of network control theory

Because network control theory is fundamentally a modeling endeavor, it is important to consider model assumptions, model validation, and model extension. First, it is important to acknowledge that the model can only be as accurate as the data used to construct it, and thus one must deal with the inherent limitations associated with constructing the anatomical network from diffusion imaging data.^{162–164} Second, when considering a linear model of system dynamics,¹⁵³ the assumption is that brain network dynamics are linear. In the brain, these linear models have preliminary support in empirically measurable dynamics,^{129,160} but further work is needed to delineate the breadth of their applicability. Moreover, it is important to note that, if using this linear approach to model nonlinear dynamics (e.g., those observed in EEG and MEG data), the assumption of linearity nevertheless remains true over short time horizons and in the vicinity of the operating point.¹⁶⁵

If one wishes to expand beyond short time horizons and states surrounding the operating point, then one must consider nonlinear models of brain dynamics.¹⁶⁶ Which nonlinear models might be relevant while remaining theoretically tractable? This is an open question, but one particularly useful approach might be to use system identification to extract the appropriate nonlinear model from real data.¹⁶⁷ Better understanding of control strategies for appropriate nonlinear models of brain dynamics could be particularly important in understanding large-scale circuit function supporting cognition. For example, synchronization dynamics are thought to play a critical role in facilitating the transfer of information between brain regions at the mesoscale,¹⁶⁸ but principles of the brain's endogenous regulation of synchronization remain far from understood. One hypothesis from theoretical physics is that these networks employ a push–pull control strategy in which antagonistic desynchronizing and synchronizing nodes regulate the transfer of information through the network.¹⁶⁹

By analyzing the functional network topology of focal and distributed (clinically known as secondarily generalized) seizures, recent work demonstrates that desynchronizing and synchronizing brain regions antagonistically regulate the ability for seizures to synchronize network dynamics.¹⁴³ Thus, control strategies like push–pull control may be relevant for homeostatic regulation of (nonlinear) synchronization dynamics in the human brain.

Beyond nonlinear extensions, other interesting questions to consider include the possibility that some regions of the state space are inaccessible or pathological,¹⁵⁴ that the brain may be underactuated in certain states,¹⁷⁰ and that control can be implemented by distributed as well as focal strategies.¹⁵⁹ Moreover, although structural controllability theory¹⁵³ is inherently built on knowledge about the structural connections in a network, it will be interesting in the future to extend these models to statistically estimate the set of either structural or extrasynaptic¹⁷¹ connections that are being utilized at a particular moment in time and how that set might change as humans perform a cognitively effortful task.

Putting it all together: neurofeedback, network neuroscience, and control

What does network control theory add to the conversation between neurofeedback and network neuroscience? Far from being a third wheel, network control theory in fact offers the theoretical framework in which to predict how the activation of a region (or connection or subgraph) by neurofeedback will affect brain network dynamics, moving the brain into a new mental state and thereby altering intrinsic cognitive processes. Thus, in essence, network control theory offers a theoretical backbone on which to begin formulating ideas about the mechanisms of cognition and begin developing theoretically grounded interventions to target their modulation.

To be a bit more concrete, one could use network control theory to simulate the impact of a change in energy at one (or several) regions (or connections) on the subsequent brain network dynamics. Using this approach, one could identify the constellation of regions and connections that—when brought to a specific pattern of activation—would have a predictable effect on brain state

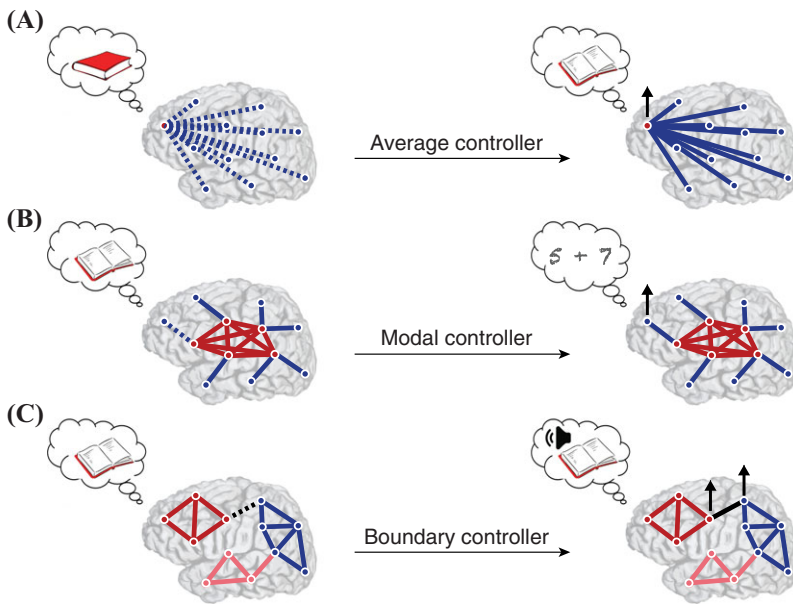


Figure 5. Self-regulating brain network controllers for cognition. Neurofeedback could be used to teach individuals how to modulate brain activity in important control points that drive changes in dynamical brain state—an experimental tool that would offer tremendous opportunities for studying “cognition dynamics,” or the ability to perform specific tasks based on the current brain state. Furthermore, this approach might be used to train individuals with specific cognitive deficits to better manage their ability to perform certain types of tasks. (A) Suppose that individuals could be trained to upregulate the brain’s average controller (red node) to assist in navigating different brain states associated with a specific task, such as opening up and reading a book. (B) If the subject has difficulty with switching between tasks—such as reading and doing math—he/she might be trained to upregulate his/her brain’s modal controller (blue node) to switch more efficiently. (C) If the subject has difficulty with comprehension or reading aloud, he/she might be trained to upregulate his/her brain boundary controllers between functional modules associated with language and speech.

(Fig. 5). Then, one could use neurofeedback to produce that pattern of activation, validate the predicted subsequent effect on brain state dynamics, and observe the associated change in cognitive function. In essence, this approach enables a closed loop between theory and experiment, providing a framework in which to develop more general theories of brain function, explain existing empirical data, suggest new directions for empirical research, and inform experimental hypotheses.

Indeed, the confluence of these three disparate disciplines—network control theory, neurofeedback, and network neuroscience—offers much promise in advancing our understanding of human cognition. Both neurofeedback and network neuroscience are well-developed fields at this point, and they are ripe for integration. Network control theory is the newest field of the three, and its integration will require careful development, characterization, and validation to reach its full promise. Nevertheless, the potential payoff in terms of obtaining a basic, mech-

anistic understanding of human cognition, seems at this point to be well worth the effort.

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Competing interests

The authors declare no competing interests.

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