Extending the Diagnostic Capabilities of Artificial Intelligence-Based Instructional Systems

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■ *Active problem solving has been shown to be one of the most effective ways to acquire complex skills. Whether one is learning a programming language by implementing a computer program, or learning calculus by solving problems, context-sensitive feedback and guidance are crucial to keeping problem-solving efforts fruitful and efficient. This article reviews AI-based algorithms that can diagnose student difficulties during active problem solving and serve as the basis for providing context-sensitive and individualized guidance. The article also describes the crucial role sensor-based estimates of cognitive resources such as working memory capacity and attention can play in enhancing the diagnostic capabilities of intelligent instructional systems.*

Computer-based educational technology has had a transformative impact in every imaginable educational context — from tablet-based educational games for preschoolers, to massively open online courses for university students and independent learners. Artificial intelligence (AI) research solutions have the potential to boost the impact of these systems by enhancing their diagnostic capabilities. For example, unlike one-on-one human tutoring, it is rare to find computer-based learning environments that not only provide opportunities for practice on complex problems (such as working on multistep algebra problems, or practicing programming by writing multiline code), but also provide contextually relevant feedback and guidance based on an analysis of individual problem-solving actions. In contrast,

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because of the technical challenge of making sound diagnostic inferences, we typically find two extremes represented in the design of instructional systems: either systems that constrain the learner by restricting allowable actions during skill acquisition (for example, multiple choice problems) or systems that provide opportunities for open-ended practice, with the only corrective feedback coming from the natural feedback inherent to the task environment (for example, a programming problem that a student solves on his or her own — with built-in feedback from the interpreter or compiler). The problem with the first extreme is that students develop skills in context and complexity that are different from their eventual application context. The problem with the latter is that students may flounder with inadequate feedback, or have incorrect or superficial strategies reinforced in the absence of corrective feedback and guidance.

These challenges point to the need for diagnostic techniques that are (1) tied to problem solving — capable of interpreting and assessing individual actions in the context of relatively unconstrained problem-solving activities (for example, writing a computer program, flying a scenario in a flight training simulator); (2) automated — reducing the need for manual intervention; (3) objective — minimizing confounds stemming from subjective biases; and (4) fine-grained — providing feedback at the level of individual problem-solving actions, as opposed to problem-solving outcome alone.

Cognitive Tutors: A Promising AI Approach

Cognitive tutors, based on the adaptive control of thought — rational (ACT-R) cognitive architecture, represent one promising approach for boosting the diagnostic capability of interactive learning environments (Anderson et al. 1995). The development of the ACT-R theory of cognition, which describes how humans perceive, think, and act, has been led by psychologist John Anderson and colleagues at Carnegie Mellon University (Anderson and Lebiere 1998). ACT-R is instantiated in the form of a programming language with primitive constructs that embody specific assumptions about human cognition. It has been used to model human performance in a broad array of complex cognitive tasks, ranging from automobile driving (Salvucci 2001) and tactical decision making (Anderson et al. 2011) to algebra and computer programming (Corbett, Anderson, and O'Brien 1995).

Cognitive model-based diagnosis is particularly well suited for environments where learners acquire skills through hands-on practice. In many complex problem-solving domains, learners have access to a broad range of problem-solving actions (operators) that can be combined to transform a problem from some initial state to a goal state through a set of intermediate problem states. In complex task domains, the number of actions students have at their disposal can be quite large. By interacting with elements of the learning environment, these actions can produce a vast set of possible intermediate problem-solving states. The primary task of the novice, learning to navigate unfamiliar problem spaces, is to reach goal states efficiently through one or more possible sequences of states. Feedback allows learners to avoid problem states that lead to dead ends and circumvent inefficient transition paths to the goal. The lack of feedback, however, can cause the student to experience frustration and confusion, and result in the adoption of suboptimal performance strategies.

The provision of feedback in cognitive tutors is based on a combination of an ACT-R model of the successful and unsuccessful strategies relevant in a given problem domain, and plan-recognition algorithms (a process referred to as model tracing). Automated plan-recognition systems try to infer an agent's plans or line of reasoning from its actions (Kautz and Allen 1986). The detailed encoding of knowledge embodied in a cognitive model allows the plan-recognition process to map student actions to successful and faulty problem-solving strategies. While student actions remain consistent with one or more fruitful problem-solving strategies, the system remains unobtrusively in the background. However, when student performance is indicative of ineffective or inefficient strategies, the system intervenes with assistance tailored to the actual issue or subtask causing difficulty for the student at that given moment. A student may also ask a tutor for hints specific to the learner's immediate problem-solving context.

Many cognitive tutors incorporate functionality known as knowledge tracing to pace students optimally through problems while distinguishing between slips and errors (that is, disambiguating between the possibility that a student knows the correct answer but presses a wrong key, and the possibility of substantive errors in understanding). Knowledge tracing relies on Bayesian estimation to characterize a student's strengths and weaknesses relative to the knowledge components in the cognitive model (Corbett and Bhatnagar 1997). Based on student actions, the system estimates the probability that a learner has mastered the component rules required to perform a task. These estimates are dynamically updated while the student performs learning tasks. Estimates from knowledge tracing can identify areas in which a student may need the most practice, providing opportunities to remediate specific skill deficiencies. Additionally, students receive feedback in the form of estimates of their mastery of various knowledge and skill components through an on-screen bar graph. Unlike many computer-based environments, which guide all students through a pre-specified sequence of problems, knowledge tracing allows students to work on problems appropriate to their competence level. Proficient students can progress quickly through to challenging problems, while students who need additional practice get to work on problems that target their particular deficiencies.

ACT-R based cognitive tutors have been shown to reduce training time by half and increase learning outcomes by a standard deviation or more in rigorous classroom and laboratory assessments (Anderson et al. 1995). They support teaching concepts ranging from programming to genetics and represent some of the most broadly used educational systems (for example, tens of thousands students in thousands of schools across the United States use ACT-R based tutors for algebra and geometry).

Opportunities for Enhancement with AI

While replications in numerous domains have shown cognitive tutors to be highly effective computer-based learning platforms, their performance falls short of one-on-one tutoring from skilled human tutors. Researchers have argued that a critical advantage of skilled human tutors over cognitive tutors is the fine-grain access they have to their student's behaviors. For instance, as Anderson and Gluck (2001) noted, a human tutor can see frustration on a student's face, hear uncertainty in an utterance and track the length of time a student takes to work through a problem. Such broad access to a learner's emotive and cognitive state, they argue, allows the skilled human tutor to display far greater sensitivity and adaptability in the tutorial interaction than current computer-based tutoring systems. To address this gap, researchers have begun considering the inclusion of capabilities to sense and estimate cognitive states that play a fundamental roll in learning, including variation in attention and working memory load. These capabilities could expand the diagnostic functionality of cognitive tutors and provide a more effective basis for pedagogical diagnosis, and guidance.

Cognitive State Sensing

As Just, Carpenter, and Miyake (2003) note, information-processing theories of cognition suggest that cognitive processes operate in a capacity-constrained environment (for example, Kahneman [1973]; Wickens [1984]). These theories posit that cognitive capacity varies across individuals and is affected by broad range of physiological and psychological factors. Capacity utilization, a metric that indicates the proportion of a resource pool engaged during a given period, characterizes how hard the cognitive system is working to produce observed performance. Meanwhile, task resource demands, the size of each individual's resource pool, and the speed with which cognitive processes execute all affect resource utilization. When demand for cognitive resources exceeds availability, cognitive efficacy is compromised: processes slow down and partial products and results of computations begin to decay, worsening performance. Individuals experience high capacity utilization as more effortful — we define the term cognitive effort as the perceptible effect of high cognitive capacity utilization. Measuring cognitive effort or capacity utilization is vital because performance that burdens available capacity processing may be brittle, and the addition of processing requirements could cause performance to fail (Wickens and Hollands 2000). Over the years, the educational research community has become aware of the negative implications of excessive cognitive load on learning outcomes. Real-time measurements of the cognitive effort experienced by an individual can guide dynamic modulation of training complexity to match a student's cognitive capacity.

A promising avenue for estimating changes in cognitive efficacy uses measurement of cortical activity to estimate the degree of cognitive effort required to perform tasks. Researchers have noted that the amplitude and spatial extent of cortical activity increases as performance becomes effortful, even as behavioral performance on tasks remains the same (for example, Hill and Schneider [2006]; McAllister et al. [2001]). This methodology could enable detection of challenging learning contexts, which require broader participation of cortical areas to produce a given level of performance. In addition to broad changes in overall levels of cortical activity, increases in cognitive effort are associated with localized changes in activity within specific cortical networks. This suggests that cortical activity can serve as the basis for making inferences about cognitive effort. Our objective at the Honeywell Laboratories Human-Centered Systems Group has been to measure ongoing cortical activity to make inferences about cognitive effort using practical and unobtrusive sensors that can be used in realistic applied and laboratory task contexts. Given these requirements for practicality and effectiveness, our efforts have largely focused on the use of electroencephalography (EEG) as a biometric measure of the user's cortical activity.

EEG measures scalp potentials generated by the combined electrical activity of billions of neurons in the brain, as tiny currents generated by signaling between neurons sum together to produce measurable voltage changes at the scalp. These signals represent a rich source of information about a broad range of neural processes. For example, analyses of EEG voltage fluctuations that consistently occur in a time-locked fashion with critical events can reveal the dynamics of perceptual and decision-making processes at a temporal resolution of one millisecond. Additionally, spectral measures of rhythmic cortical activity within characteristic frequency bands serve as a useful source of information about

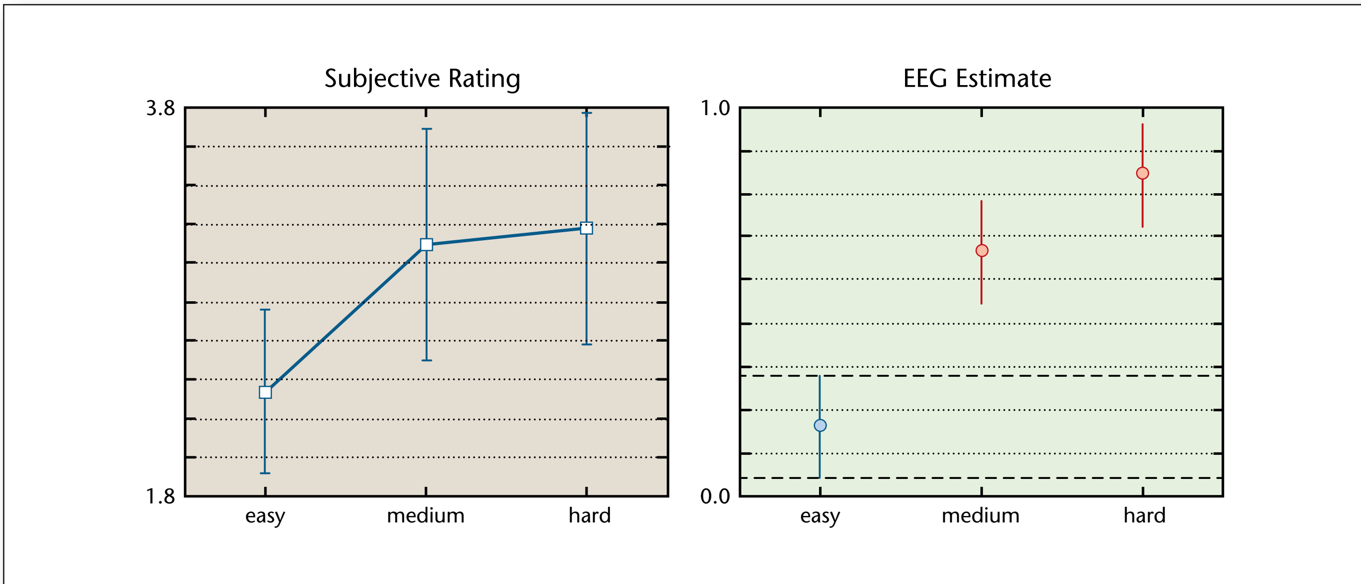

Figure 1. Ratings by Pilots Landing Helicopters in Three Different Scenarios.

Left: Subjective cognitive effort by pilots. *Right:* EEG-based estimates of cognitive effort of the same pilots in the same scenarios.

temporally stable cognitive activity, such as attention and working memory. While EEG provides information about cortical neural activity, several other methods can also estimate changes in brain function. Broadly used alternatives have major practical limitations, however. For example magnetic resonance imaging (MRI) systems, which offer excellent spatial resolution, but have high per-use costs, rely on slow changes in blood flow (hemodynamics) as an indirect measure of neural activity, and are impractical for use in most clinical and operational settings. Other measures of cerebral hemodynamics, such as functional near-infrared spectroscopy (fNIRS) and transcranial Doppler (TCD) are typically designed to measure activity in relatively small regions of the cortex and, therefore, typically limit spatial coverage. Additionally, systemic changes in vascular activity can confound interpretation of signals from these sources. Though electrophysiological sensors such as electrocardiogram (ECG) and electro-dermal response (EDR) can also provide insight into cognitive effort, noncognitive factors such as physical activity and stress can strongly influence measures derived from these information sources, and they have relatively poor temporal resolution compared to EEG.

Modern, lightweight, relatively inexpensive EEG sensor systems can offer excellent temporal resolution capabilities for measuring ongoing cortical activity. Depending on the number of sensors and their distribution on the scalp, EEG systems can provide useful information about activity distributed across a wide range of cortical regions. Researchers have observed distinct patterns of EEG activity in response to variations in task demands. For instance, activity in the alpha band (8 to 12 hertz) is dominant when an individual is awake, but resting. Activity in the beta band (13 to 30 hertz) becomes prominent when cognitive effort increases. While these general observations provide an approximation of brain activity in response to task demands, complex interactions between rhythmic brain activity at different frequencies and brain locations during cognitive task performance also exist. For example, Meltzer et al. (2008) examined cognitive load-related changes in the EEG power spectrum and its spatial distribution in the context of the Sternberg task (a short-term memory task requiring recall of a sequence of letters). They noted that power increases in the gamma band (> 40 hertz) occurred throughout the brain as the length of the letter sequence increased, but observed that these increases occur most prominently in the occipital lobe. They also found that both alpha and theta band activity increased in the frontal midline cortex and decreased in the occipital cortex, concurrently with increased gamma range activity in these regions. These observations argue against viewing power in any given frequency band as a unitary phenomenon and call for viewing variations in activity in different brain regions. Consequently, we use statistical machine-learning techniques to characterize the unique pattern of discriminating activity for each individual in response to variations in cognitive effort. Given the complex distribution of spectral power across frequency bands and cortical locations, we rely on these techniques to create multivariate discriminant functions that identify an optimal subspace projection of the data to discriminate between different levels of effort. These discriminant functions, constructed using task calibration with systematically varied task demands, accept high-dimensional EEG data as input, and produce a single-dimensional estimate of effort. EEG data collected in this context can then be used to create a discriminant function for use in similar contexts to estimate effort. This method can create both individual and group data models; however, the discriminant functions exploit the optimal features for a given individual (increasing accuracy), while the latter (group model) approach supports contexts where a baseline may not be available.

We have applied these techniques to estimate cognitive effort in a range of complex operational environments — from commercial flight decks (Mathan, Feyereisen, and Whitlow 2007) to ground-based infantry operations in urban environments (Mathan et al. 2007). For example, professional helicopter pilots performed a flight simulator evaluation of a display designed to help pilots land in poor visibility conditions by executing landings in three different landing contexts of varying difficulty. Pilots' ratings of perceived cognitive effort, as measured by the NASA-TLX mental demand rating (figure 1, left) were closely correlated with EEG-derived measures of cognitive effort (figure 1, right).

In another study, we examined whether EEG-based measures of effort exceed the specificity and sensitivity of alternate methods of estimating cognitive effort; these include subjective ratings, a secondary reaction-time task, and heart-rate variability. Data were collected in two conditions (with corporate jet pilots as participants) in a flight simulator under four conditions: two low-effort cruise conditions, and two high-effort approach conditions. Scores associated with all measures were normalized to lie between 0 and 1 (figure 2). Given the stark differences in the information-processing requirements associated with these two tasks, we would expect the two plots on the left of each graph in figure 2 (cruise) to share little overlap with the two bars on the right of each graph (final approach). However, as the extent of overlap between the Hi and Lo workload bars for each of the conditions indicates, the EEG measure has much higher specificity and sensitivity than other measures, as indicated by the receiver operating characteristic (ROC) values and overlap of box plots.

EEG-based estimates of cognitive effort can also detect subtle variations in cognitive effort among individuals coping with acquired (treatment-related) cognitive impairment (Mathan et al. 2010). Five survivors of brain cancer and five survivors of breast cancer participated by reading text of varying complexity under different levels of time pressure as a cognitive load. Unlike prior evaluations that provided stark difference in cognitive load stimuli to improve classifier performance, the subtle workload variations explored in this study more closely represented the variations in cognitive load one might encounter in activities of daily living. Analysis revealed that user workload could be classified using an EEG-based index, with an accuracy (ROC area) of 0.84 (SD = 0.03). The analysis of this data also showed that the EEG sites that contributed to the peak classification outcome were most densely concentrated over the left hemisphere (figure 3), which includes regions that play a critical role in language processing.

Some of our earlier research has demonstrated that even when outside the controlled environment of a laboratory or flight simulator, we can reliably estimate cognitive effort when using modern biometric sensing devices. Honeywell originally developed technology aimed at EEG-based cognitive state estimation for operational settings in the context of the Defense Advanced Research Projects Agency (DARPA), improving warfighter information intake under stress (also called Augmented Cognition) program. Using a combination of data from a wireless EEG sensor system (Advanced Brain Monitoring, Inc., Carlsbad, CA), and the machine-learning approaches described earlier, we successfully demonstrated the efficacy of our approach at the U.S. Army Aberdeen Proving Ground (figure 4) where military trainers explicitly manipulated participant cognitive load between high and low levels of effort in a high-fidelity battlefield training exercise. The system classification accuracies exceeded 0.80 (ROC area) in this within-subjects cross-validation analysis context (Mathan et al. 2007).

Collectively, these results suggest that the EEG index described here provides a sensitive and specific measure of cognitive effort in a broad range of contexts, from battlefield simulations to aircraft piloting, as well as reading tasks. Spatial analyses indicate that the features driving the observed results are consistent with neuropsychological theory, and comparisons to other measures of cognitive effort highlight the stronger performance of the EEG-based metric.

Attention Estimation

The process of acquiring a novel skill typically begins with a period of declarative instruction when a student learns about the central facts or concepts associated with a domain. Computer-based learning environments typically facilitate declarative instruction through video clips or online textual expositions. Research has shown failure to manage and appropriately direct attention toward processing declarative information, which likely compromises the robustness and accuracy of encoded declarative knowledge (Anderson 1993). Poor encoding of declarative knowledge can impede skill acquisition, and declarative knowledge of the central concepts in

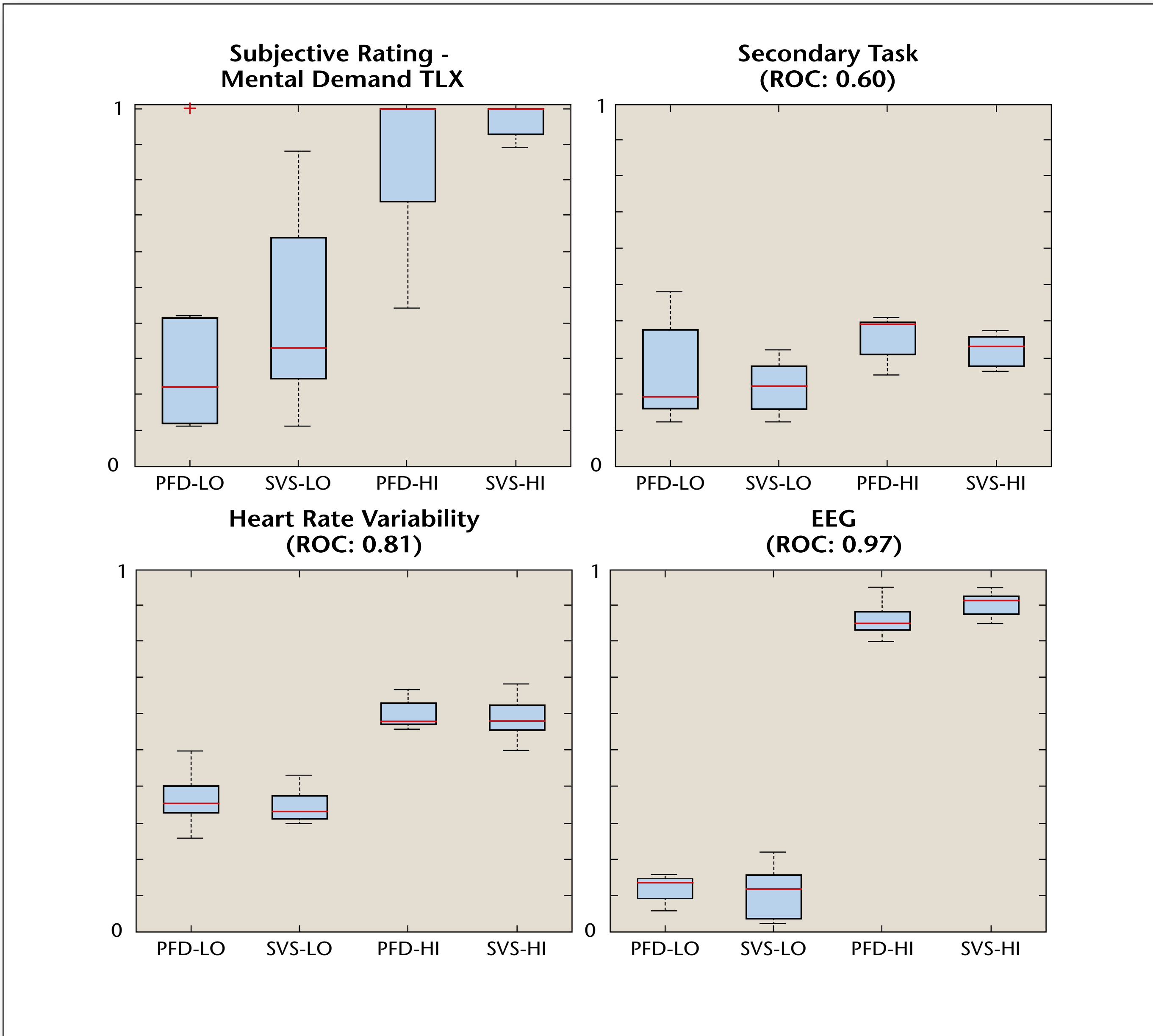

Figure 2. Comparing EEG Measures of Effort to Subjective Ratings, Secondary Task.

HRV (heart rate variability).

a domain serves to structure early problem-solving attempts (Anderson 1993). This encoding requires both sustained attention and active elaboration strategies such as self-explanation, both of which are difficult to maintain over long periods of time. For instance, Smallwood and Schooler (2006) observed subjects over the course of a 45-minute reading task. Subjects were interrupted at random and asked if they were still on task. Their research revealed that learner's "zoned out" for close to 20 percent of the time during reading tasks. Real-world estimates of mind wandering tend to be even higher (Killingsworth and Gilbert 2010). Such lapses in attention over the course of reading text and watching video expositions can impair the skill-acquisition process. Learners may miss critical information that could be of importance in subsequent problem-solving efforts.

Research suggests that oscillatory EEG activity — particularly in the alpha frequency band (8–12 hertz) — can index variations in attention. Parieto-occipital alpha power and subjective reports of attentional

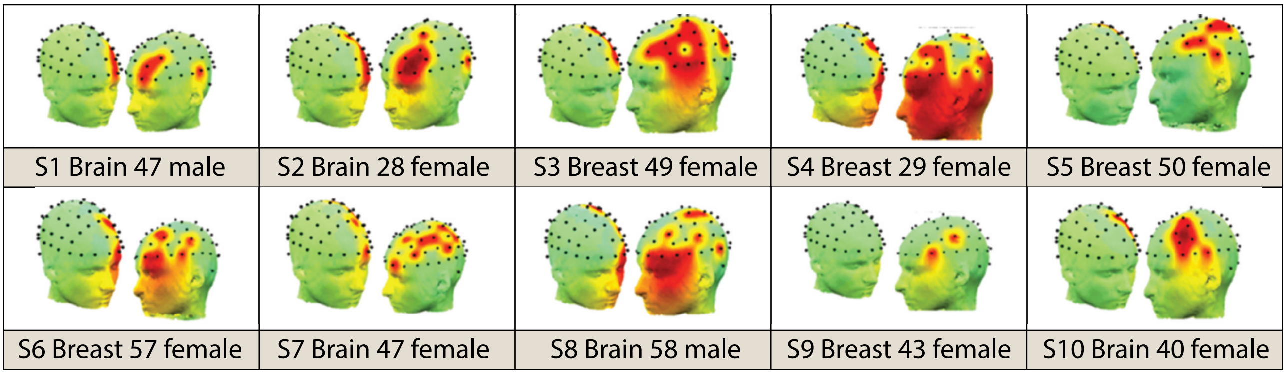

Figure 3. Contour Map of Sites Identified Using Feature Selection Techniques to Discriminate Between Brain Activity Associated with High and Low Difficulty Text.

Study involved brain and breast cancer survivors.

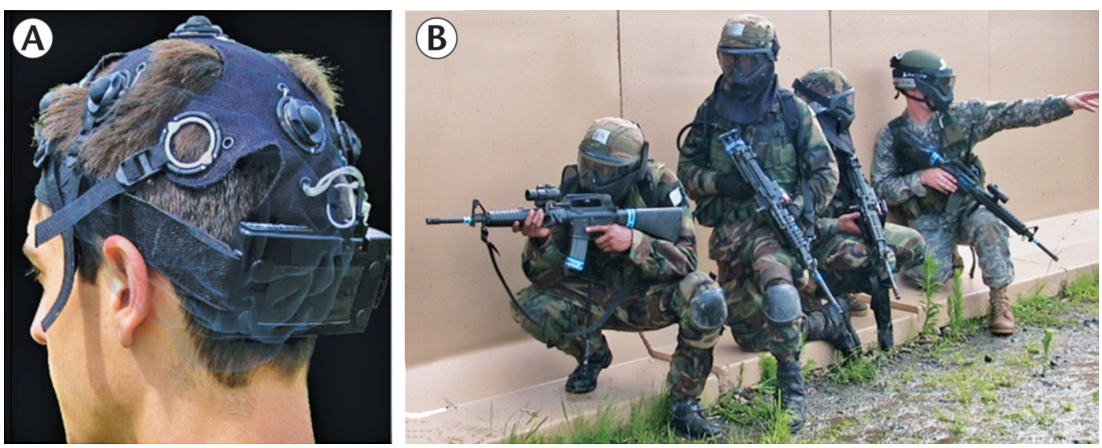

Figure 4. Demonstration of Honeywell Cognitive State Sensing Technology at Aberdeen Proving Ground.

EEG activity was measured using low-density wireless EEG sensors (left).

state are both associated with visual attention and awareness. For example, the authors of this article explored the relationship between alpha activity and participants' introspective judgments of attentional state as each varied from trial to trial during performance of a challenging visual detection task. We collected participants' subjective ratings of perceptual decision confidence and attentional state on continuous scales on each trial of a rapid serial visual presentation detection task while recording EEG. We found that confidence and attentional state ratings were largely uncorrelated with each other, but both were strongly associated with task performance and poststimulus decision-related EEG activity (Macdonald, Mathan, and Yeung 2011). Crucially, attentional state ratings were also negatively associated with prestimulus EEG alpha power: periods of low attention were associated with high levels of alpha oscillations, and vice versa. Attesting to the robustness of this association, we were able to classify attentional state ratings through prestimulus alpha power on a single-trial basis (figure 5). Moreover, when we

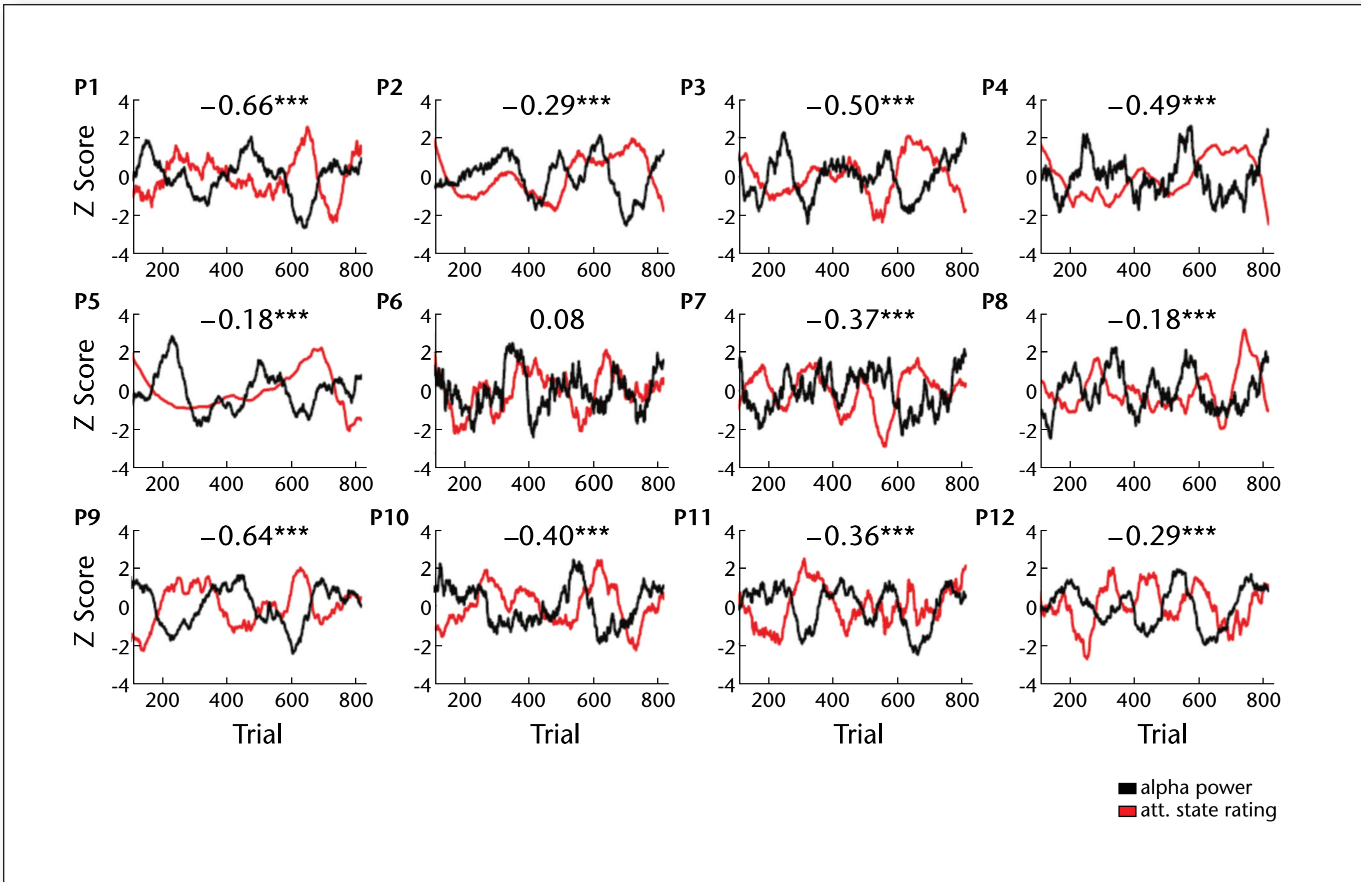

Figure 5. Data from 12 Subjects Showing the Relationship Between Alpha Power and Subjective Ratings of Attention During a Target Detection Task.

Black lines: alpha power. Red lines: subjective ratings of attention.

repeated these analyses after smoothing the time series of attentional state ratings and alpha power with increasingly large sliding windows, both the correlations and classification performance improved considerably, with the peaks occurring at a sliding window size of approximately 7 minutes worth of trials. Therefore, our results suggest that slow fluctuations in attentional state in the order of minutes are reflected in spontaneous alpha power. Because these subjective attentional state ratings were associated with objective measures of both behavior and neural activity, they can provide a simple and effective estimate of task engagement as the basis for AI assistance in operational settings that require human operators to maintain a sustained focus of visual attention.

Conclusion

This review supports the feasibility of making reliable estimates of cognitive state in a wide range of application contexts. However, the practicality of EEG data collection in training and operational environments has limited the development of EEG-based instructional applications. The time required to configure large arrays of sensors, restrictions on movement associated with cables, and mess associated with conductive gel or saline electrolytes represent significant user inconveniences that have largely restricted the use of EEG systems to research settings. However, in recent years several technology developments, including dry contact sensors from Wearable Sensing, Inc. (San Diego, CA), a dry electrolyte gel from Advanced Brain Monitoring, Inc., both of which can provide a mess-free conductive medium, and consumer-oriented systems from NeuroSky, Inc. (San Jose, CA), and EMOTIV, Inc. (San Francisco, CA) promise to support EEG data collection, signal classification, and estimation of cognitive effort and attention in training and tutoring environments. These systems eliminate wires and transmit EEG data over wireless radio connections, simplify donning and doffing of sensors, improve comfort, and provide integrated data logging and processing capabilities to enhance the practicality of EEG systems.

Real-time estimates of cognitive state can help in tutorial interaction in several ways. Attention often lapses when learners watch video or read text passively, which hampers skill acquistion. Mitigation strategies triggered by cognitive state classifiers could minimize the negative impact of low attentional states during declarative instruction. For instance, when the intelligent automated cognitive tutor detects low attentional state in a student during presentation of online text or video, the system could intervene and step the student through the material with interactive prompts. These prompts could present questions related to concepts just covered and give students the chance to respond using multiple-choice responses. Additionally, the system could index text or video segments presented during low attentional states and prompt students to revisit these segments at a later time.

Neurophysiological assessments of working memory can provide augmentation of hands-on practice by dynamically matching working memory demands imposed by the learning environment with a student's working memory capacity. For instance, the grain size of instructional content could dynamically vary the level of assistance or scaffolding provided to students following errors during practice based on neurophysiological assessments of cognitive state (Anderson et al. 1995). Students experiencing high levels of cognitive load would receive instructional scaffolding to step interactively through the series of subgoals necessary to accomplish a problem-solving objective and maximize learning performance. In contrast, students experiencing lower cognitive load levels could simply be reminded of the overall problem-solving goal, leaving negotiation of the underlying problem space and its maintenance in memory to the student. As a student becomes more proficient at performing tasks, the working memory resources associated with task execution normally diminish. The intelligent tutor system could detect this change and modulate workload levels to adapt the pace or complexity of the task environment to the learner's working memory capacity to maximize learning and retention.

These examples highlight promising avenues for creating closed-loop neural feedback systems that could accelerate learning through individually tailored training. Each example is based on current technologies and existing theories about the cortical underpinnings of cognitive functions. We can expect the impact of neurotechnology on AI-based tutoring systems to only increase as the technology is refined — or revolutionized — as research uncovers ever more sensitive and nuanced indices of the cognitive processes of interest.

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