Opportunities for Case-based Reasoning in Personal Flow and Productivity Management

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Abstract. Knowledge workers can benefit from tools to support them in performing deep, concentrated work. Research in biofeedback has shown success in training relaxation, but not in directly influencing task performance. One reason for this may be the difficulties users have in contextualizing biofeedback signals for different task situations. This presents an opportunity to leverage the strengths of case-based reasoning to select the feedback mechanism that will produce the best response. This paper describes initial research into the Adaptive Choice Case-Based Reasoning (ACCBR) system, that learns from and interacts with a user to assist them in achieving greater concentration and productivity.

Keywords: neurofeedback, EEG, flow, CBR

1 Introduction

By some estimates, there are currently more than 1 billion knowledge workers in the world [1]. Knowledge work includes "non-routine cognitive jobs" that require considerable amounts of concentration and creativity to perform. This work benefits from long stretches of uninterrupted work, resulting in feelings of "flow", where work is simultaneously challenging, engaging, and enjoyable [2].

There are numerous productivity enhancement tools available to assist knowledge workers in keeping track of tasks, appointments, and other necessities of their work life [3]. However, there is little work on developing tools to support workers in achieving and maintaining flow states for longer periods of time.

There have been numerous studies on neurofeedback therapies for a variety of conditions and diseases [4]. Specifically for the task of increasing the frequency and duration of deep, concentrated work, neurofeedback may provide the information necessary for the correct feedback signals to be delivered.

Figure 1a shows how standard neurofeedback is used by an operator performing a task. The operator must make choices based on task demands, and then update their mental state based on the new task state and the rewards received. The operator then must integrate the neurofeedback signals with task feedback signals in order to improve task performance, which could end up being a divided attention task.

The Flow Choice Architecture (FCA) is being developed to integrate the mental state and task performance of a knowledge worker in order to suggest "nudges" that can help the knowledge worker enter and remain in flow. Nudges are external aids such as rituals, sounds, speech, or other "mental hacks" that subtly encourage behavior change [5]. If FCA classifies worker biosignals as distraction, it may "nudge" the user by showing task completion lists, highlighting the days work schedule, or verbalizing encouragement [6].

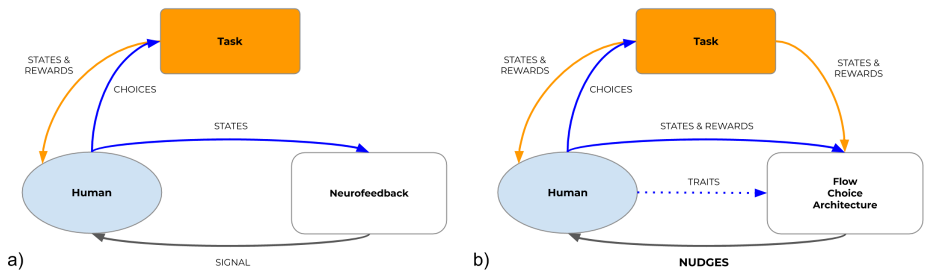

Fig. 1. (a) The user must integrate feedback from the task environment and neurofeedback. (b) The FCA observes the human and task states and reward signals to generate task-relevant nudges.

Figure 1b shows the interaction of the FCA with the knowledge worker as they perform their tasks. The mental and task states and rewards are used by the FCA to determine if a nudge is warranted. This information, including if there were previous nudges, is taken into account to determine the step most likely to influence the knowledge worker to enter flow. Nudges that have little effect on the operator's mental state will be selected less often than those that have a rapid and positive effect.

2 The Challenge Addressed

This domain features several difficult characteristics that CBR research can address with effective solutions. First, the domain requires *individualization*. The problem of motivating increased deep, concentrated work is inherently personal. The nudges that work for one person will not necessarily work for another, requiring personalization for each user. CBR case creation based on user experience provides a natural way to gather this personalized knowledge.

Second, the domain requires *context*. Although the structure of electroencephalogram (EEG) signals enables accurate tracking of user mental state, it does not contain enough information to determine the feedback signals needed to motivate increased performance. Contextual information such as time, task, and work history are also needed to determine a correct nudge. Cases provide a natural way to associate other information with the EEG signal, such as time of day, time spent working, task undertaken, operator traits, etc, to fine-tune the effectiveness of nudges. This may be an ideal representation for both storing and retrieving this contextual information.

Finally, solutions in the domain have *uncertain effects*. Nudges will be effective less than 100% of the time, meaning that even if the FCA makes the "correct" choice in nudges to suggest, the user may not give the desired response. By retrieving a set of cases similar to the current EEG, task, and context, the nudge suggestions made in FCA by the Adaptive Choice Case-based Reasoning (ACCBR) system can examine a range of alternatives and reason effectively about the exploration - exploitation tradeoff.

3 Background Research

3.1 Measuring Operator State

Evaluation of operator state was traditionally performed with subjective measures based on interviews or questionnaires, where participants assessed their state during or after a task [7]. These approaches depend on opinions of participants reported on subjective scales, and do not always assure reliable, comparable results. An alternative approach involves the monitoring of operator state using psychophysiological measures such as EEG, heart rate variability (HRV), electrodermal activity (EDA) and breathing rate.

Machine learning methods have been combined with feature selection techniques to measure a subject-independent operator workload or cognitive effort needed to perform a task [8]. Thejaswini et al. [9] used a channel-wise Support Vector Machine (SVM) classifier to detect emotional state, and achieved average classification accuracies of 79% (SEED dataset) and 76% (DEAP dataset).

3.2 CBR for Neurofeedback

Case-based reasoning has been successfully applied to the study of EEG signals in several studies. Cai et al. [10] investigated classification of depression using case representations containing four computed characteristics of EEG signals and seven other demographic features of the test subject. Using feature weighting and KNN as the retrieval mechanism, they were able to achieve a 91.25% accuracy in diagnosing depression in patients, significantly improving on 81.44% accuracy for EEG data alone and 88.97% from a previous study.

An integration of decision trees and CBR was used in [11] to classify patient EEGs into one of seven different psychological or physical disorders, including migraines and ADHD. Their work showed that even a very coarse discretization of EEG signals in conjunction with psychological and behavior features can produce accurate classification of different disorders.

Like these systems, ACCBR computes features from the raw EEG signals and combines them with other information to construct a case to be classified.

However, ACCBR differs from these system in that the determination to make nudges is a continuous process, happening throughout the working day. This creates hundreds or thousands of case applications, allowing for continued learning and updating of the case base. In this sense, it is more similar to the continuous case-based reasoning work of [12].

4 ACCBR Description

ACCBR is one implementation of the "Nudge Controller" shown in Figure 2. The purpose of ACCBR is to determine if the current mental and task state suggests that the operator would benefit from a nudge to achieve or remain in deep, concentrated work. To do this, it continually balances the stream of classifications of the EEG signals generated by the user with task and historical information to result in a decision to produce a nudge or to remain silent.

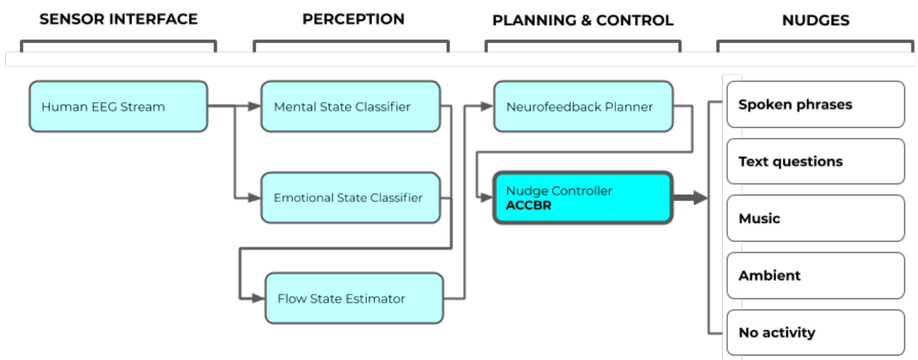

Fig. 2. Pipeline architecture of the neurofeedback-driven FCA where the modules process data on server and client threads in parallel.

4.1 ACCBR Cycle

The FCA begins with user demographic and trait information [13], knowledge of the task and task rewards and then begins on that task. FCA observes the operator and task state, and classifies the EEG signals being collected into on of the standard quadrants of the valence arousal scale, labeled: $neutral$, sad, $fear$, $happy$. When the classification has high confidence (i.e., when the same classification has been made several times in a row), it is combined with the task state and other contextual information to create a probe into case memory.

The probe will return one to five cases from case memory and a response based on the returned cases is generated. The response depends on the distribution of responses and the history of previous nudges. The nudge is executed, and FCA monitors operator state to determine the effectiveness of the nudge. The measurement of effectiveness comes from the transition of mental states to a more positive mental state and from the task completion status. This process continues until the end of work tasks or the operator is mentally fatigued.

5 Example of EEG Classification

Perhaps the most risky aspect of our approach is the belief that we can consistently and accurately classify EEG signals into one of the four bins indicating mental state (emotions). To alleviate this risk, we conducted an experiment to test the FCA EEG classification, which will directly affect our ability to collect high-quality cases.

In the experiment, we used the SEED-IV dataset, which contains EEG recordings from 15 participants that conducted 72 video clip trials that evoked one of four emotions: $neutral, sad, fear, happy$. Noise and artifacts such as blinks and jaw clenches were filtered from the raw EEG data and then segmented into 4-second epochs without overlap. A Fourier transform on each segment produced power spectral density (PSD) features in 5 frequency bands which were then reduced to three components using a Linear Discriminant Analysis (LDA) transformation that maximized the separability among the classes. These three components were classified using a densely-connected three-layer neural network. The dataset of 1,080 trials was randomly split 70:30 into training and test sets i.e. 756 and 354 trials respectively and run 10 times. Figure 3 shows the confusion matrix for the average of 10 runs of the experiment, which produced an average overall classification accuracy of 99% on the test trials.

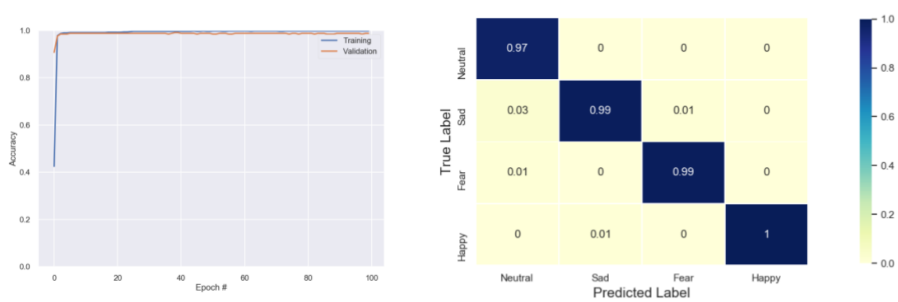

Fig. 3. Left: Training & validation set accuracy. Right: Confusion matrix.

6 Conclusions and Future Work

Our next steps in this research are to collect one- to three-hour sessions of users performing deep cognitive work tasks to determine the range of variability between users. We will use these sessions to develop individualized case bases and determine where additional efficiencies can be found.

While this is early-stage work, the EEG classification results already obtained and the methodology developed to contextualize the EEG signals shows promise for the development of a productivity tool that will support deep cognitive work.

We believe that many of the problems that are faced when working with neurofeedback and biofeedback systems in general can be addressed using the tools and techniques that are available in the case-based reasoning community. CBR systems have unique capabilities for knowledge acquisition and replay that are directly applicable to domains where there is significant uncertainty, where there are no general rules that will apply to all users, and where the signals collected on a continuous basis must be augmented with context in order to be effectively interpretable.

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