Augmented Cognition using Real-time EEG-based Adaptive Strategies for Air Traffic Control

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Future air traffic systems aim at increasing both the capacity and safety of the system, necessitating the development of new metrics and advisory tools for controllers' workload in real-time. Psychophysiological data such as Electroencephalography (EEG) are used to contrast and validate subjective assessments and workload indices. EEG used within augmented cognition systems form situation awareness advisory tools that are able to provide real-time feedback to air-traffic control supervisors and planners. This augmented cognition system and experiments using the system with air traffic controllers are presented. Traffic indicators are used in conjunction with EEG-driven cognitive indicators to adapt the traffic in real-time through Computational Red Teaming (CRT) based adaptive control mechanisms. The metrics, measures, and adaptive control mechanisms are described and evaluated. The best mechanism to improve system efficacy was found when the system allowed for real-time adaptation of traffic based on engagement metrics driven from the EEG data.

INTRODUCTION

The air traffic control (ATC) system has the primary role of assuring a safe and efficient management of air traffic flow. Human factors research investigates the best way for the human air traffic controller (ATCO) to operate. Such investigations help in delivering the required ATC services of the future (Durso and Manning, 2008).

Eliminating an activity from the ATCO's list of activities through automation would not necessarily reduce the ATCO's workload (Hopkin, 1971). For example, automation introduces activities that do not exist when the ATCO is relying on manual processing. Automation may inhibit the ability of a person to detect critical signals and warnings (parasuraman et.al., 1996), and can even produce new types of errors and increase workload (sarter & Woods, 1995).

Conflict among workload indicators (Hopkin, 1971) need to be monitored to assess whether or not load-balancing problems arise as one indicator decreases while another increases. Continuous monitoring of these indicators provides a first layer for a system-level safety net. A further step is to identify appropriate maneuvers to adapt and steer back the system to some desired states when required.

Attempts to continuously monitor workload with the purpose of adapting automation to optimize the operator's workload - "adaptive aiding" or "adaptive automation" (Rouse 1988) - have been the context of Human Factors research since the 1970's. Rouse (1998) discussed the two building blocks for an adaptive aiding system to work: Human performance monitoring and on-line assessment methods. The former relies on the current state of task demands, the available human information-processing resources, and human sensorimotor resources. The latter provides information on what the human is doing and intend to do, to augment the prediction process of human performance.

Psychophysiological measures – such as Electroencephalography (EEG) - play two important roles in adaptive automation (Byrne and Parasuraman, 1996). First, they can make available information on the impact of different automation forms to enhance the associated adaptive logic. Second, psychophysiology can take measurements from the human operator and integrate these measurements with models of the operator and performance measures to improve the way automation gets regulated.

Attempts to use psychophysiological measurements in adaptive aiding were made, but a critical discussion (Scerbo et.al., 2003) of these attempts diverted interest away from this concept. Scerbo et.al. (2003) argue that brain-based measures should satisfy two minimum conditions before they function as a trigger to change modes of automation. First, the measures need to be sensitive enough as a diagnostic tool. Second, they should reflect those environmentally induced changes that are reflected in behavior. The two conditions culminated overtime in a new concept, Augmented Cognition.

Augmented cognition (Stanney et.al., 2009) tightly couples a computer and a user performing a task through physiological and neurological sensors. The tight coupling is achieved through three components: cognitive state sensors, adaptation strategies and control systems. Continuous monitoring of the task, EEG and the environment enables real-time validation of the implementation of an augmented cognition system.

The majority of augmented cognition systems rely on a threshold or simple classification to trigger an adaptation strategy. This can lead to the "yo-yo" effect (Diethe, 2005). When a threshold is exceeded, a response is triggered, which then pushes the stimuli back under the threshold; then, within a short time frame, the threshold is exceeded again, and consequently, the response is triggered again. These short cycles of on and off responses can increase workload. To overcome this problem, simple fixes were adopted including turning off adaptation after a fixed time, ensuring a minimum time between cycles, or maintaining adaptation 'on' after the first time it is triggered. Stanney et.al. (2009) conclude that ``little research has been done to develop sophisticated approaches to determine how physiological measures can best be used to control closed-loop systems".

One major challenge facing the design of robust control strategies in augmented cognition is the highly dynamic and non-linear nature of the environment. Very similar actions can lead the same air traffic situation to many diverse states. Air traffic simulators can overcome part of this challenge with their abilities to simulate future states of the system (ie performing system-level look-ahead and what-if analysis). The control mechanism can then rely on optimization techniques to select the best adaptive strategy to be implemented, given the current traffic and the operator's cognitive state.

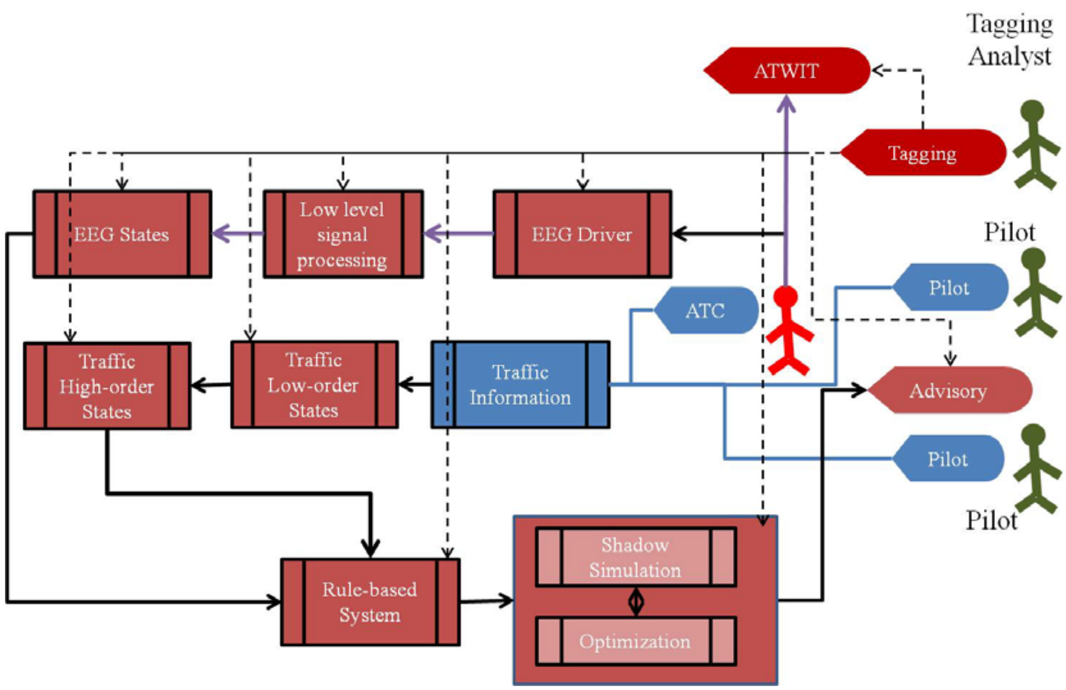

Figure 1: The Adaptive Logic of the Real-time EEG-Based Augmented Cognition System

METHODS

Augmented Cognition Design

A high level design for the augmented cognition system used in the current study is provided in Figure 1. As the ATCO interacts with the traffic scenario, her EEG data is captured, recorded, analyzed, and high-order engagement indicators were calculated in real-time. Simultaneously, the traffic is analyzed to extract traffic related complexity metrics in real-time. Both EEG and traffic indicators are used in a rule-based system, which decides if there is a need for adaptation. Once such need is established, the adaptive control mechanism is triggered.

The experimental environment consists of three players: an ATCO controlling the measured position, and two pilots. The traffic was sufficient for one pilot to handle. Consequently, the two pilots were assigned the additional role of acting as an auditory advisory system to the ATCO as well. Maneuvers proposed by the adaptive control strategy need to be communicated to the ATCO. Pilots played this additional role of communicating the proposed maneuvers to the ATCO. This provided a safety net to ensure that information are communicated in clear human voice. A text to speech system could have been used, but the impact of an automated auditory advice on the ATCO would have added an extra experimental variable.

Adaptive Control Strategy

The adaptive control system is designed using the Computational Red Teaming (CRT) design principles. CRT achieves adaptation through the use of simulation and optimization algorithms to discover maneuvers to counteract complexity. This is achieved by recursively estimating and searching for counteractions maneuvers for the complexity in the environment. More information about CRT can be found in Abbass et.al. (2014).

The integrated optimization and simulation modules enabled dynamic identification of an adaptive strategy, which is optimized over a look-ahead time. The set of allowed maneuvers in the optimization are as follows:

1. Request Direct to waypoint XXX for aircraft A

2. Request 2000ft climb or descent for aircraft A
3. Request emergency landing for aircraft A
4. Aircraft A turn 5º right or left … wait 2 minutes … Aircraft A resume original path
5. Increase or decrease speed for aircraft A to XXX
6. Stop responding to any communication about aircraft A

where, "XXX" and "A" representing a waypoint and an aircraft chosen by the optimization engine, respectively.

ATWIT Technique

The FAA ATC Workload Input Technique (ATWIT) (Stein, 1985) is used to obtain subjective assessment of workload from the ATCO every two minutes. ATWIT works on a scale from 1 to 10, where '1' indicates minimum workload, while '10' indicates maximum workload. A screen with 10 buttons colored from dark green (1) to dark red (10) illuminates every 2 minutes. If no response is received for 20 seconds, the buttons disappear. ATWIT was explained to all ATCOs and they were all familiar with the concept.

EEG Indicators

The high temporal resolution provided by EEG signals can be monitored in real-time to assess the operator cognitive state and validate it against workload metrics. An EEG signal is normally split into different bands. The following is a common setting, although discrepancy in the literature exists in the exact value of the lower and upper bound of each band: Delta (1-4 Hz), Theta (4-8 Hz), Alpha (8-12 Hz), Low Beta (13-21Hz), SMR (12-15 Hz), High Beta (20-32 Hz), and Gamma (32-42 Hz).

Appropriate combinations of these bands can form indices to be correlated and checked-against traffic states. Pope et.al. (1995) compared among four indices, while Freeman et.al. (1999) followed similar steps and identified that the ratio of Beta to Theta and Alpha $\frac{\beta}{\alpha+\vartheta}$ is the most effective in their experimental environment. Using this ratio is possible for post-analysis. However, in real-time environments, it is important to use ratios which are bounded to reliably guarantee the stability of the adaptive control system.

One such ratio that satisfies the condition of being bounded and is not too different from the one above is the Theta-Beta-Ratio. Montgomery et. al. (1998) used this ratio in a study among a group of bright, normal, young adults, where they found that Theta to Beta ratio increased during eye open as compared to eye closed conditions. More importantly, neurofeedback research indicated that an increase in Theta-to-Beta ratio above 3 may indicate a slow wave disorder. For normal persons, the ratio will always fall between 0 and 3, setting around 1.5 for many people.

Psycho-physiological Recording and Analysis

Nineteen EEG channels distributed according to the 10-20 standards, whereby sensors are 10% or 20% spread apart on the scalp, were recorded in real-time, with 2 references and 1 ground.

The data arriving from each EEG electrode are analyzed to extract spectrum information. Each EEG signal is analyzed into the seven frequency bands.

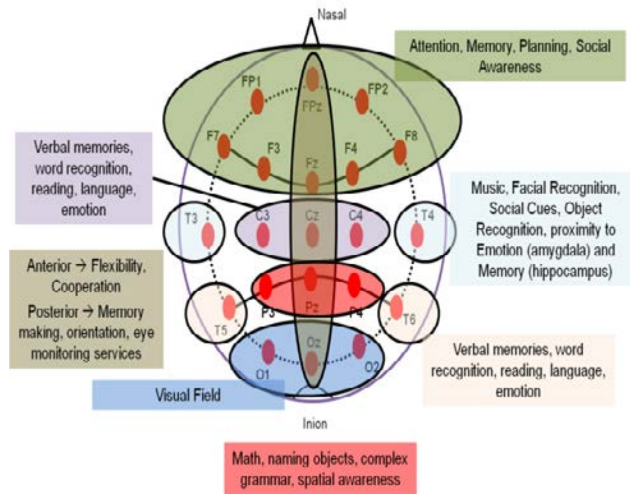

Figure 2: The layout of EEG sensors and their corresponding mental functions. Matching colors will associate the text boxes with the corresponding positions.

The grouping in Figure 2 estimates mental processing for situation awareness, planning, and attention. Two engagement metrics were used in the assessment of mental models. The first metric was based on Theta to Beta ratio. The second metric captured the change of high beta over time in the frontal cortex.

Task Complexity

The complexity of traffic was measured using the index proposed in (Sridhar et.al., 1998). Twenty other basic measures on traffic were collected for post-analysis.

EXPERIMENT PROTOCOL

Participants

Four ATCOs with an average experience of 20 years were chosen. The same two pilots were used for the whole week of the experiments. They were both males with 550 and 5000 hours of flying experience, respectively.

Baseline Protocol

Baseline information was collected at the start of each session for each ATCO. The performance of an ATCO in a session is measured relative to his unique baseline performance at the start of that session. The experimental protocol commenced with three baselines conditions for 2 minutes each, at the start of a session and repeated again at the end of each session. The three conditions were: eyes-closed relaxed, eyes-opened relaxed, and eyes-opened with computation.

The direction of change in neural firing in different brain regions between eyes-opened-with-relaxation and eyes-opened-with-computation provided cues for mental processing accompanying problem solving activities. The computation task during eyes open with computation that was given to each ATCO was a Sudoku puzzle. They were all familiar with this puzzle before. To solve a Sudoku puzzle, the human requires visual scanning to establish situation awareness of the numbers in each row, column and square. It also requires simple arithmetic (domain propagation) to estimate the missing number (Mount et.al. 2012, Tuček et.al. 2012).

The direction of information only relied on eyes-opened conditions. This is to avoid differences in lighting conditions

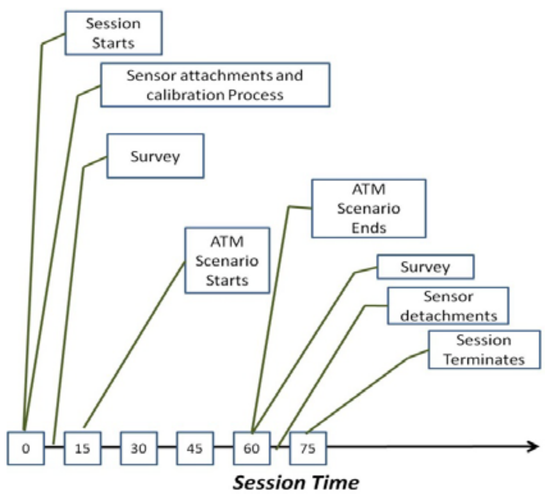

Figure 4: Timeline of Experimental Protocol

that may occur when comparisons are done between eyes-closed and eyes-opened conditions, which can cause instability of the adaptive control strategy.

Experimental Design

The experiments were conducted over five days with the four subjects. A traffic case representing a typical day (not too high- or too low-complexity) was used. The scenarios were counter-balanced.

Four scenarios were used:

A. Adaptation is not activated; therefore not used
B. Adaptation is activated by task complexity indicators alone
C. Adaptation is activated by cognitive complexity indicators alone
D. Adaptation is activated by both task complexity and cognitive complexity indicators

Each session lasted about 75 minutes. Each session started with a pre-session survey, 6 minutes of EEG pre-session baseline equally distributed among eye-closed, eye-opened, and eye-opened with computations, an ATC simulation for 50 minutes, 6 minutes of EEG post session baseline equally distributed among eye-closed, eye-opened, and eye-opened with computations, a post session NASA TLX (NASA, 1986) questionnaire with some additional questions, and a post session survey.

During the first 25 minutes of an ATC simulation, the objective of automation was to increase complexity, while in the last 25 minutes, the objective was to decrease complexity.

RESULTS

ATWIT Results

The ATWIT results (Table 1) represent the average and standard deviation of the scores chosen by the ATCO in each scenario. The higher the value, the more an ATCO perceived that the situation is complex.

Scores for the first 25 minutes of the scenarios were similar regardless of whether adaptation was used or not. During the last 25 minutes of the scenarios, the scores were different.

Table 1: ATWIT average scores in the last 25 minutes of an ATC simulation.

Scenario	Complexity Scores
No adaptation	3.79±1.05
Adaptation triggered by task complexity alone	5±1.07
Adaptation triggered by EEG alone	2.5±1.38
Adaptation triggered by both task complexity and EEG	3.40±1.38

The most notable difference is between the scores of the two cases of adaptation when task complexity is used alone and when EEG is used alone. ATCOs perceived the first case to have double the complexity of the second (ρ=0.048).

TLX Results

TLX (NASA, 1986) is a subjective workload rating technique developed by NASA Ames. The six questions in this technique were used in conjunction with additional questions related to complexity at the start, middle, and end of the scenario.

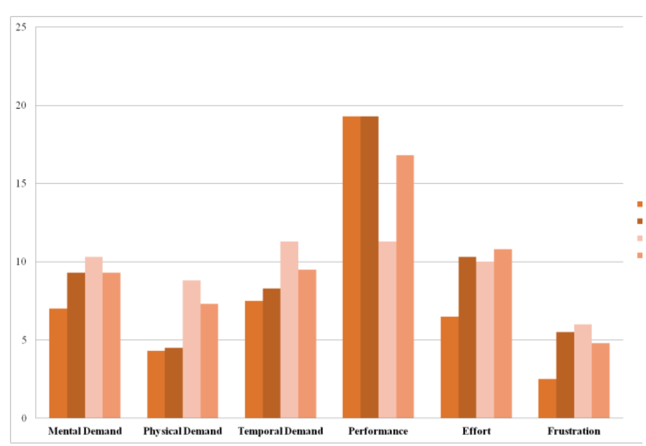

Figure 3: NASA TLX average rating for each scenario.

In all cases where adaptation is used (Figure 4), the subjects saw the task to have a higher mental, physical, and temporal demand, and higher level of frustration. Nevertheless, they rated their performance to be best when adaptation was triggered using the EEG indicators.

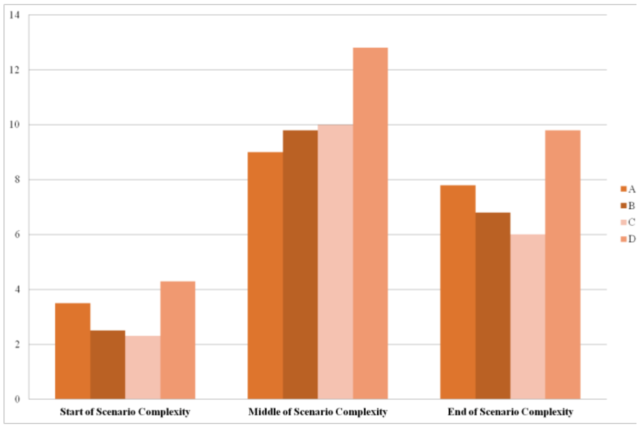

Figure 5: Additional questions average rating for each scenario.

The extra questions added to the classical TLX questions concern the complexity of the scenario at the start, middle and end. While participants rated the middle of a scenario to be slightly higher in complexity (Figure 5) when adaptation with cognitive indicators was used, the rating of complexity for the end of scenarios was lowest when adaptation with EEG indicators was used.

These findings support Hopkin's (1971) example of the conflict that may exist among workload indicators. In the sessions when adaptation was used, more commands were issued by the advisory system to the controller. While perceived complexity according to ATWIT reduced and performance of controllers according to TLX were better, the increase in communication impacted controllers' perception of mental, physical, and temporal demands; more communications with the controller led to more ``perceived" complexity for controllers when asked at the conclusion of a scenario.

CONCLUSION

EEG signals were analyzed in real-time to extract mental cues and task complexity indicators were extracted as traffic complexity cues. Both types of cues were used to guide the adaptation process to balance complexity in the session.

A computational red teaming (CRT) adaptive control strategy is used with a look-ahead ability to evaluate consequences of a particular adaptive strategy on the air traffic environment. CRT relies on simulation and optimization algorithms to challenge the environment by searching for optimal maneuver strategies to counteract complexity in the environment. Adaptation is triggered by workload cues extracted from the traffic, cues extracted from changes in the EEG, or by both. Augmented cognition is demonstrated whereby EEG cues reduced complexity. Controllers found their performance to be better in the scenarios when EEG cues were used to trigger adaptation than those scenarios when adaptation was not used or was triggered with workload cues alone. However, more work and experiments are needed to continue evolving the complexity of adaptive control in the presented augmented cognition system.

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