Computer Teammates: Should They Read Your Mind?

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Abstract

The present paper describes recent work with a type of automation that is adaptive in nature. In systems that use adaptive automation, the level of automation, the number of automated systems, or the format of the interface can be modified in real time. Often, these systems behave like computer teammates. Attention is focused on two types of adaptive automation: 1) behavior-based and 2) a brain-based systems. Recent research on these systems is described and the findings are discussed with respect to performance and user acceptance.

Introduction

Computer systems have evolved considerably from the first main frame batch processing systems of the 1950s. Initially, computer systems were developed for large businesses or organizations to perform simple mathematical operations on many similar records of data. Today, they are omnipresent in our society and perform countless varieties of functions. In addition to managing data and information, computers are used for word processing, email, communication, entertainment, training and education, and to maintain the safe operation of complex systems. And yet, even with the breadth of applications that have emerged over the last 50 years, one aspect of computer systems has changed very little. They are still largely subservient to humans. That may change, however, with the development of computer systems that use adaptive automation.

Automation

Automation has been described as a machine agent that can carry out functions normally performed by humans (Parasuraman and Riley 1997). These can be entire functions, activities, or subsets thereof. There are several benefits to automation (Wickens 1992). It can perform functions that are beyond human capability, it can perform functions that humans do poorly, and it can perform those functions that humans find bothersome or a nuisance. The nature of automated systems can vary widely. Sheridan and Verplank (1978) described a range of systems that varied from completely manual to fully automatic. In between these extremes are semiautomatic systems that differ in the degree of autonomy the automation has in executing functions and communicating with the operator.

Adaptive Automation

Unlike traditional automation, adaptive automation refers to systems in which the level of automation, the number of automated systems, or the format of the interface can be modified in real time (Scerbo 1996; 2001). More important, however, changes in the state of automation can be initiated by either the human or the system (Hancock and Chignell 1987, Rouse 1976). Parasuraman, Bahri, Deaton, Morrison, and Barnes (1992) have argued that adaptive automation allows for a tighter coupling between the level of automation and the level of operator workload.

To date, several large-scale efforts have been undertaken to demonstrate adaptive automation. In the mid 1980s, the Defense Advanced Research Projects Agency (DARPA), Lockheed Aeronautical Systems Company, McDonnell Aircraft Company, and the Wright Research and Development Center developed the Pilot's Associate. The Pilot's Associate was a network of cooperative knowledge-based avionics systems capable of monitoring internal and external events, informing the pilot of potential actions the system might take, and presenting the pilot with the appropriate information, in the proper mode, at the right level of detail, at the appropriate time (Hammer and Small 1995).

More recently, the U.S. Army explored the feasibility of adaptive automation in their Rotorcraft Pilot's Associate (RPA) program (Colucci 1995). This effort expanded upon the previous one by attempting to develop and demonstrate an intelligent "crew member" for the next generation attack helicopter. The heart of the adaptive automation system for the interface was the Cockpit Information Manager (CIM; Miller, Guerlain, and Hannen 1999). This system was designed to make inferences about current and impending activities, allocate tasks among crew members and the aircraft, and reconfigure cockpit displays to support the crew's ability to execute those activities. The CIM allocated the best mix of tasks between crew members and the system. It determined the most important information to present on limited display spaces and where to locate pop-up windows. Appropriate symbology could be added or removed from displays and the amount of detail could be adjusted to desired levels. Moreover, the CIM allowed crew members and the system to coordinate the task

allocation process and communicate their intentions. Initial user evaluations indicated that the system appeared to behave like a junior crew member and often performed according to user expectations.

Authority

One of the important issues surrounding adaptive automation concerns authority. Who should have control over changes among the modes of operation? Several individuals have argued that operators should always have authority over the system (Billings and Woods 1994; Malin and Schreckenghost 1992). The Pilot's Associate and RPA were both designed to be subordinate to the user. Developers of tutoring and other associate systems have also followed the "user in charge" principle (Bushman, Mitchell, Jones, and Rubin 1993). Many of these arguments have been based on work with life critical systems in which safe operation is of utmost concern. However, Scerbo (1996) has argued that in some hazardous situations where the operator may be vulnerable, it would be extremely important for the system to have authority over automation invocation. For example, it is not uncommon for many of today's fighter pilots to sustain G forces high enough to render them unconscious for periods of up to 12 seconds in an armed and fast moving aircraft. Conditions such as these make a strong case for system-initiated invocation of automation.

It is not clear, however, that strict user authority over changes among automation modes is necessary or even desired for other types of adaptive computer systems. Some researchers have argued that there may be times when the operator is not the best judge of when automation is needed. For example, changes in automation may be needed at the precise moment the operator is too busy to make those changes (Sarter and Woods 1994; Weiner, 1989). Further, Inagaki, Takae and Moray (1999) have shown mathematically that the best piloting decisions concerning whether to abort a take-off are not those where either the human or the avionics maintain full control. Instead, the best decisions are made when the pilot and the automation share control. Consequently, the remainder of this paper will describe research with adaptive systems in which authority over the automation is shared and neither the user nor the system has sole control over invocation.

Methods for Invoking Automation

One of the key issues for adaptive systems with shared authority concerns how changes among states or modes of automation are accomplished. A variety of techniques can be used to invoke the automation. For instance, changes among modes of automation could be tied to the occurrence of specific events that occur in the task environment. For example, states of automation in a commercial aircraft might change based upon proximity to the destination. Alternatively, models of operator performance or workload could be used to drive the adaptive logic (Hancock and Chignell 1987). For example, Rouse, Geddes and Curry (1987, 1988) describe a system in which an operator model is designed to estimate current and future states of an operator's activities, intentions, resources, and performance. Information about the operator, the system, and the outside world are sent to an intent module that interprets the operator's current actions with respect to his or her goals. A resource module estimates current and future demands and another module uses this information to predict current and future levels of performance and to determine the need for adaptive aiding. (For a more thorough discussion see Parasuraman *et al.* 1992). Another approach would be to assess operator performance in real time and use deviations from acceptable ranges to invoke the automation. Last, an adaptive system could use psychophysiological measures to trigger changes among the modes of automation. These last two methods that will be discussed in more detail below.

A Behavior-Based System

It is possible to use real-time measures of operator performance to trigger changes in automation. This approach was studied by Krahl and Scerbo (1997) who examined the performance of individuals paired with either a computer or human partner. The participants were asked to perform a pursuit tracking task that was partitioned so that one individual controlled the vertical movement of a cursor and the other controlled its horizontal movement. The participants were assigned to one of three different teams. In one of these teams, two participants worked together to perform the task. In the other two teams, the participants shared control with a computer. Half of the participants worked with a computer that exhibited expert-level skills and the remaining individuals worked with a computer exhibiting novice-level skills. The participants were told to obtain their lowest overall team score derived from a combination of the scores from both teammates. On a given trial, if an individual thought that he or she could do better than their partner, they could press a button on their joystick and attempt to take control of both axes. Control over both axes would be permitted only if the individual had demonstrated superior performance on the previous trial. Similarly, if the computer outperformed the participant on the previous trial it would usurp control of both axes on the next trial. Otherwise, each partner retained control of his or her axis. If control over the axes changed on a given trial, it would revert back to both partners on the subsequent trial. Thus, the task can be considered adaptive because the level of automation on a given trial was determined by the participant's performance on a previous trial.

Krahl and Scerbo (1997) found that performance depended upon group assignment. Individuals paired with the novice computer performed more poorly than any other group. On the other hand, those paired with the expert computer performed quite well at the outset and eventually reached the level of the computer expert itself. Differences between the expert and novice computer conditions were particularly noteworthy because any time the computer

took control of both axes, the participant lost control and had less opportunity to practice the tracking task. Krahl and Scerbo found that in the novice condition, the human and computer teammates each took control of both axes equally often. In the expert computer condition, however, humans managed to take control from their computer teammate on only 3% of the trials. By contrast, the computer expert took control from the human teammate on 34% of the trials. Thus, the human teammates in this condition attained their superior level of performance with 1/3 less opportunity to practice the task. Scallen and Hancock (2001) have also reported similar findings with a simulated flight task. Taken together, these findings indicate that it may be feasible to implement adaptive automation around real-time measures of behavior and that operator performance may be enhanced through adaptive mechanisms.

A Brain-Based System

Another strategy for implementing adaptive automation would use psychophysiological measures to trigger changes among the modes of automation. Several researchers have discussed the advantages of such a system (Byrne and Parasuraman 1996; Parasuraman *et al*. 1992; Scerbo *et al*. 2001). For instance, psychophysiological measures, unlike many behavioral measures, can be obtained continuously. Further, there may be many times when an operator is engaged in considerable cognitive activity, but very few overt responses (e.g., button presses) are required. Also, psychophysiological measures can provide additional information beyond behavioral measures alone when the two measures are coupled.

There are many psychophysiological indices that reflect underlying cognitive activity, arousal levels, and external task demands. Some of these include cardiovascular measures (e.g., heart rate, heart rate variability, blood pressure), respiration, ocular motor activity, and even speech (see Byrne and Parasuraman 1996; Kramer and Weber 2000; Scerbo *et al*. 2001 for a review). One of the more promising candidates is EEG. Numerous studies have shown that EEG is sensitive to differences in cognitive workload and can be used to distinguish among tasks (see Scerbo, Freeman, and Mikulka, in press).

Recently, Pope, Bogart and Bartolome (1995) described a closed loop, brain-based system for adaptive automation. In this system, changes in automation modes are triggered by the operator's own EEG signals. More specifically, the system uses an index of engagement based upon ratios of EEG power bands (alpha, beta, theta, etc.). The EEG signals are recorded and sent to a LabView Virtual Instrument that determines the power in each band for all recording sites and calculates the engagement index used to change the automated components of the operator's task. The system recomputes the engagement index every two seconds and changes the task if necessary.

Freeman, Milkulka, Prinzel and Scerbo (1999) studied this brain-based system with several participants who were asked to perform a monitoring, resource management, and compensatory tracking task simultaneously. All tasks remained in automatic mode except the tracking task which shifted between automatic and manual modes. Performance was examined under both negative and positive feedback conditions. Under negative feedback, the tracking task was switched to or maintained in automatic mode when the engagement index increased above a pre-established baseline. By contrast, the tracking task was switched to or maintained in manual mode when the engagement index decreased below the baseline. The opposite schedule of task changes occurred under the positive feedback conditions. Freeman et al. argued that the system should moderate workload and result in better performance under negative feedback. These investigators found that tracking performance in the manual mode did indeed improve under negative as compared to positive feedback. Similar findings were also found in subsequent studies with individuals who performed the task over much longer intervals (Freeman *et al*. 2000) and under conditions of high and low task load (Prinzel *et al.* 2000).

In another experiment, Cunningham, Scerbo, and Freeman (2000) studied the relationship among EEG engagement indices, the ability of individuals to maintain attention over an extended period of time, and daydreaming. Participants were asked to perform a monotonous task requiring them to monitor the repetitive presentation of pairs of lines on a computer display for 40 minutes. Occasionally, the length of the lines would increase. The participants were told to press a button whenever they detected a pair of longer lines. During the course of the monitoring session, the participants were also told to report their daydreaming activity. Specifically, they were asked to press the space bar on the computer's keyboard whenever they realized they had been thinking about something other than the task at hand. Cunningham and his colleagues hypothesized that differences in the engagement index ought to be observed immediately before and after participants indicated they had been daydreaming.

The results showed that on the whole, participants detected fewer pairs of longer lines and reported more instances of daydreaming over the course of the monitoring session. This pattern of findings suggests that it became more difficult for the participants to focus attention on the task over time. In addition, Cunningham and his colleagues (2000) examined the value of the engagement index during the 30-second intervals immediately preceding and following the point at which participants reported their daydreams. They found that the value of the engagement index increased immediately after the report of a daydream suggesting that the participants were re-engaging in the task.

Taken together, the findings from these studies suggest that it is possible to obtain psychophysiological indices of an individual's mental activity and use that information to drive an adaptive system. Further, it is also possible to use a brain-based, closed loop system to

moderate an operator's workload.

Although one might question the practicality of using EEG or other psychophysiological measures in any real world application, the US Navy has studied this possibility as a means of protecting pilots in high performance aircraft. It is not uncommon for pilots of military aircraft to be subjected to a number of stressors including heat and G forces. These effects are compounded by flight suits that provide protection against chemical and biological agents and the use of anti-G garments. Consequently, research has been aimed at an integrated life support system that incorporates physiological sensors for eletrocardiogram (ECG), blood-oxygen content, electromyogram (EMG), electroencephalogram (EEG), and respiratory activity. The Smart Aircrew Integrated Life Support System (SAILSS) program is designed to use physiological measures of the pilot to help maintain life support and operate the environmental controls. Consequently, the availability of an integrated life support system such as this will soon permit incorporation of adaptive automation technology based upon physiological indices.

Although initial results from research with the brain-based system of adaptive automation show promise, it should be recognized that several critical conceptual and technical issues must be overcome before such a system could be fielded. As Scerbo et al. (2001) indicate there are still issues surrounding the sensitivity and diagnosticity of psychophysiological measures that need to be addressed. Also, Kramer (1991) has argued that psychophysiological measures can be confounded with other sources of noise. There are also significant technical problems that need to be solved such as making recording equipment less obtrusive and reducing artifacts in the signals. Further, from a more general perspective the use of EEG still rests on the following assumptions: 1) that EEG can be used as an index of arousal or attention, 2) that variations in arousal and attention reflect variations in mental workload, and 3) that variations in task parameters which affect mental workload can be related to variations in EEG (Scerbo *et al.* 2001). Further, Hettinger, Branco, Encarnacao, and Bonato (in press) argue that valid and reliable psychophysiological measures must be not only tied to knowledge of the operator's activities, but also to the context in which those activities are carried out.

Acceptance of Computers as Teammates

An obvious question concerns the acceptability of adaptive automation or more broadly, computer teammates. How readily will humans accept computers as partners? In one study, Nass, Fogg and Moon (1996) found all that was needed for humans to accept a computer as they would a human partner was the perception of interdependence. In their study, individuals were asked to exchange information regarding the value of several items in a hypothetical survival task with a computer partner. Half of the participants were told their performance would be evaluated independent of their computer partner. The remaining participants were told they would be evaluated as a team and that their performance depended upon their computer partner. Although the computer's responses were the same under both conditions, the participants rated their computer partners as more cooperative, knowledgeable, friendlier, and more like a human when they perceived their interactions to be interdependent. In another study, Jones and Mitchell (1995) found that users readily allocated activities to an intelligent associate system designed to support supervisory ground control of satellites. Miller, Guerlain, and Hannen (1999) also reported that a group of pilots who worked with the RPA found it to be very useful and that it often provided the right information at the right time. Moreover, in the initial tests no pilot chose to turn off the RPA.

Collectively, the studies described above show that people may be perfectly willing to accept computers as teammates. However, Scerbo (1996) has argued that the user interface for an adaptive automation system is apt to have a significant impact on its overall effectiveness. Specifically, an adaptive system that relies on only one method of information exchange (e.g., a mouse and keyboard) will place severe limits on the quality of communication between the human and the system. In an effort to examine the importance of communication in adaptive automation, Bubb-Lewis and Scerbo (2002) studied the effects of different levels of communication on task performance with a simulated adaptive interface. Participants worked with a "computer" partner to solve problems using a commercial travel planning software package. The computer partner was actually a confederate in another room who interacted with the participants according to a strict set of rules dictating when and how to intervene to complete the next task for the participant. Four conditions were studied that differed in the level of restriction placed on communication ranging from context sensitive natural language to no communication at all. The results showed that the participants' ability to complete their tasks diminished as restrictions on communication increased. Further, as communication became curtailed the computer intervened more often and ultimately led the participants to rate their experiences as less favorable. These findings suggest that the full potential and acceptance of adaptive technology may not be realized with less natural modes of interaction.

Should a Computer Read your Mind?

Thus far, most of the work in adaptive automation has addressed life critical systems in which the safety of the operator, the system itself, and customers of the system's services is paramount. The technology can certainly be applied other activities where the consequences of human error are less severe. Given the studies described above, adaptive automation could be particularly useful when incorporated in systems aimed at training and skill development. Entertainment and games are another logical possibility.

The research described above shows that it is

technically feasible to create systems that can react to, and in some cases, anticipate a user's thoughts and intentions. Although current systems are somewhat crude, as the technology evolves one can expect future adaptive systems to be more reliable.

Turning the calendar ahead some years, systems that can monitor user performance, learn and adapt to user patterns of behavior, anticipate user intentions, and respond proactively will be commonplace. Potential applications might be a personal assistant, butler, tutor, secretary, or receptionist. The success of such systems will depend upon the ability to predict a user's wants and needs with some acceptable level of reliability.

It is important to understand, however, that all of these applications would be based upon one fundamental assumption: that the individual freely consents to having his or her intentions assessed. All may be well and good when the system responds appropriately, but what happens when the system responds inappropriately? Does an error represent a user intention that was not carried out or executed incorrectly by the system or does it represent a lapse or slip on the user's part that was executed correctly by the system?

Perhaps the key to understanding the future of adaptive technology lies not with more sophisticated models of operator behavior, but with a better appreciation of interpersonal interactions between humans. Consequently, the more important question may not be whether it is appropriate for a computer to read an individual's thoughts, but whether anyone has the right to read another's thoughts.

People in our society take their right to privacy seriously. There are strict laws which govern when it is permissible to record another person's behavior. Legal scholars continue to weigh the need to protect society as a whole against the need to preserve individual privacy. However, technological innovation forces us to continually reevaluate these needs.

Consider facial recognition technology for example. These systems can quickly scan video images of thousands of people, extract perceptual invariants of facial features, compare them against a database, and under ideal conditions make a correct identification with better than 95% accuracy (Blackburn, Bone, and Phillips 2001). The potential of this technology to be used and abused recently made headlines when fans gathered for the Super Bowl learned that the City of Tampa, FL had operated a facial recognition system in a public area without their knowledge. Proponents of such systems argue that their use in public areas can help prevent crime and give law enforcement authorities the opportunity to screen large numbers of people efficiently and match them against files of fugitives and targeted individuals stored in criminal databases. Opponents of systems deployed in public areas argue that they are unreliable, can easily be abused to track ordinary individuals, and have not been validated in preventing crime (Agre 2001).

One can easily see how similar arguments might be made for and against a system that could read one's mind. On the one hand, the creation of systems that could access an individual's intentions either directly or indirectly might significantly boost operator performance in situations where the proper timing and scheduling of activities is critical. On the other hand, if an operator consented to use such a system his or her performance would be a matter of record, but what about intentions that were not carried out? Would the operator forfeit his/her right to privacy for ideas not expressed or executed?

The development of adaptive automation represents a qualitative leap in the evolution of technology. As Scerbo (1996) has noted, users of this technology will be faced with systems that are qualitatively different from those available today. These systems will certainly be more complex. Further, their performance will be more variable triggered by inconsistencies in user behavior. Consequently, the users' experiences with these systems are apt to be less like working with a tool or machine and more like interacting with a coworker. Thus, issues such as training, communication, and social and motivational factors will be far more critical than they are in present day systems.

Moreover, the challenges facing designers of such systems are not trivial. Current system analysis, design, and evaluation methodologies are likely to be inadequate. In fact, in Hammer and Small's (1995) review of Pilot's Associate program they argued that an understanding of how humans share tasks and information was more valuable than standard human factors methods and techniques. As noted above, predicting actions based upon knowledge of intentions is not straight forward. Further, Scerbo (1996) argued that researchers and designers of adaptive technology would also need to understand social, organizational, and personality issues as well. Last, there are numerous ethical issue that cannot be ignored as this type of technology continues to evolve.

Fortunately, adaptive automation is still in its infancy. This gives designers, cognitive engineers, and psychologists a chance to address the broader range of issues that surround adaptive automation before the technology is widely implemented. Clearly we have much to learn about this new form of automation.

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