

Augmenting Cognition: Reviewing the Symbiotic Relation Between Man and Machine

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Abstract. One of the goals of augmented cognition is creation of adaptive human-machine collaboration that continually optimizes performance of the human-machine system. Augmented Cognition aims to compensate for temporal limitations in human information processing, for instance in the case of overload, cognitive lockup, and underload. Adaptive behavior, however, may also have undesirable side effects. The dynamics of adaptive support may be unpredictable and may lead to human factors problems such as mode errors, ‘out-of-the-loop’ problems, and trust related issues. One of the most critical challenges in developing adaptive human-machine collaboration concerns system mitigations. A combination of performance, effort and task information should be taken into account for mitigation strategies. This paper concludes with the presentation of an iterative cognitive engineering framework, which addresses the adaptation strategy of the human and machine in an appropriate manner carefully weighing the costs and benefits.

1 Introduction

Since the industrial revolution, when men and machine started to work together, people aimed at an optimal performance of the human-machine system. Initially, during the first ages during and after the revolution, optimizing performance meant improving the machine or automated component. However, since the introduction of the personal computer and the turbulent developments in the decades afterwards, the human operators became the critical component in the human-computer system, leading to the comprehension that optimization of the interaction starts at design time. Literature describes different taxonomies which explain the *static* relation between an operator and a machine. For example, Fitts [1] was one of the first to acknowledge that both entities have different aptitudes. Fitts crafted a list describing where each entity excels. Following this approach, allocation is based on the aptitudes of each entity lead-

ing to categorized list of whether the human, machine, or a combination should implement this function [2].

The Fitts list provides an excellent insight into the aptitudes of each though it was not intended to incorporate *dynamic* situations and the list assumes the aptitudes to be static and other problems have been reported [3]. In reality the environment or context of the operator can change very rapidly creating a different demand for aptitudes. This leads to the conception that function allocation should not be fixed at the design state, but should fluctuate over a continuum of levels. In the last couple of decades a number of different dynamic function allocation taxonomies have been proposed. Sheridan & Verplank [4] presented a ten-level taxonomy that explained the division of work between the human and machine, and how they collaborate. Endsley, on the other hand, [5] suggested a taxonomy in the context of expert systems to supplement human decision-making. Endsley [6] redefined their taxonomy since they required a model that was “*wider applicable to a range of cognitive and psychomotor tasks requiring real-time control within numerous domains*”. The latest and widely accepted taxonomy [7] suggests to apply automation to four broad classes of functions. Within each of these types, automation can be applied across a continuum of levels of automation (i.e. from fully manual to fully automatic) depending on the cognitive state of the operator.

Adaptive automation (AA) takes the dynamic division of labor between man and machine as a starting point. The term adaptive automation [8], dynamic task allocation, dynamic function allocation, or adaptive aiding [9] all reflect the real-time dynamic reallocation of work in order to optimize performance. It is based on the conception of actively aiding the operator only when human information processing limitations emerge and assistance is required in order to overcome bottlenecks and to meet operational requirements. The concept of augmented cognition (AC) extends the AA paradigm by explicitly stating the symbolic integration of man and machines in a closed-loop system whereby the operator’s cognitive state and the operational context are to be detected by the system [10].

Currently, a state-of-the-art document that highlights opportunities and possible pitfalls of AC lacks in the scientific community. We strongly believe that it is important to evaluate the fast expanding ideas around the AC paradigm that compensates real-time for temporal limitations in human information processing. This paper reviews past and present research on the topic of the symbiotic relationship between man and machines starting with the static Fitts list, explaining the latest mitigation strategies, and finalizing with an iterative engineering methodology that takes into account the benefits and costs of the adaptation behavior of man and machine.

2 Potential benefits and risks of augmented cognition

For an effective and resilient human-machine system it is not wise to automate as many tasks as possible. Although machine performance is superior in some aspects; software and hardware is not always reliable (e.g. [11] [12]). Because of this, the human is often allocated the role of supervisor that can intervene when automation fails. This because humans are thought to learn more quickly and to out-perform machines

in performing tasks in novel or unforeseen situations, e.g. intervening when machines do not function as intended. Unfortunately, humans demonstrate a degraded ability to intervene when kept out-of-the-loop too long: problems with vigilance, complacency, situation awareness, knowledge and skills-degradation may be observed [13]. To overcome these out-of-the-loop performance problems, a system that augments cognition is required to take the human in-the-loop. The human can be taken in-the-loop in situations of underload; when the additional demand for human attention does not exceed the resources the human has left available. Alternating high levels of automation in which the operator becomes a passive monitor with active involvement has shown to improve situation awareness and response to errors [14] [15].

Dynamically engaging humans may solve out-of-the-loop performance problems and may be useful in routine situations in which the demand for human attention is low. This solution is not desirable in all conditions: compared to alternating levels of automation, static automation of tasks frees-up more attention that can be allocated to concurrent tasks Kaber & Endsley [16]. Further, when multiple tasks demand human attention concurrently another problem becomes more urgent. In emergency situations, humans may become absorbed in some tasks, while ignoring others and performance on these latter tasks may degrade. For an effective and resilient human-machine system a decrease in human engagement needs to be compensated for by an increase in machine involvement. In the case of overload, when the demand for attention or speed exceeds the human ability, timely involvement of the machine in task execution is desirable. A number of studies [17] [18] [19] [20] or [21] have demonstrated beneficial effects.

The expected benefit of adaptive automation is that humans and machines can be taken in and out of the loop when needed. By dynamically allocating tasks to human or machine, the performance of the human-machine system is guaranteed despite disturbances in the ability of its components and despite changes in environmental demands. Unfortunately, there are also some risks associated with adaptive automation. A mayor risk is increased complexity combined with undesirable machine behavior. Although some of the complexity of adaptive automation may be hidden and not be a problem when the system always provides the right support at the right time in the right way, the potential benefits of adaptive automation turn into risks when the system wrongly concludes that support is or is not needed or when the timing of support is wrong (e.g. [22]). Unwanted interruptions, mode errors, or automation surprises may disrupt performance and may lead to errors of omission or commission, frustration, distrust, disuse, and rejection of the adaptive system. When the adaptive system is not reliable and the human has an additional layer of automation it has to monitor we create rather than solve problems. Whether this risk becomes real depends on the context-dependent ability of adaptive automation to make the decision *whether*, *when*, and *what* to automate. This will depend on the specific application and domain.

Another risk is that humans adapt to the new situation with adaptive automation in a way we do not expect or desire (e.g. [23]). Human may not use adaptive automation as intended. They may rely too much or too little on adaptive automation and for instance fool the system such that it mistakenly thinks that the human operator needs to be taken out or in-the loop. Thus also when the human shows unreliable behavior the potential benefit of adaptive automation may turn into an additional source of risk.

It is clear the potential benefits and risks of adaptive automation are context-dependent. It will depend on the specific implementation and context of use whether a system of human plus adaptive automation will be more or less effective or resilient than a system of human plus non-adaptive automation. Although it is too early to draw general conclusions, it is worth to investigate the conditions under which the potential benefits or risks of adaptive automation will be observed and to investigate how risks can be managed. One way to cope unreliable adaptive automation may be to make machine reasoning observable and adjustable. This would allow to human to understand the system and would enable him to give the system more or less room for intervention.

3 Mitigation triggers

The basis for the AC argument is the real-time aiding of man to compensate for temporal limitations in the human information processing capacity. The previous section listed some studies that revealed beneficial effects of getting the operator out-of-the-loop in case a system augments an overloaded operators and involving the operator in the operational process when a state of underload is augmented. Assuming that machine assistance should be kept at lower levels unless high workload precludes effective human performance, AC will optimize the symbiotic relation between man and machine in an environment where the workload is varying [24]. One of the challenging factors in the development of a successful AC concept concerns the question of *when* changes in level of automation must be effectuated. Workload generally is the key concept to invoke such a change of authority, but most researchers agree that *“workload is a multidimensional, multifaceted concept that is difficult to define. It is generally agreed that attempts to measure workload relying on a single representative measure are unlikely to be of use”* [25]. Mental workload can be defined as an intervening variable similar to attention that modulates or indexes the tuning between the demands of the environment and the capacity of the operator [26]. This definition highlights the two main features of workload, which are the *capacity* of operators and the *task demands* made on them. Workload increases when the capacity decreases or the task demands increase. As stated, both the capacity and task demands are not fixed entities and are affected by many factors. Measurement workload is again much debated and we would like to elucidate the relationship between workload, task demands and performance. According to Figure 1, an operator can experience different levels of workload dependent on the task-demands. It also shows that the performance does not necessarily decline as the operator experiences a high workload. One can keep performance on a maximum level by increasing effort. However, problems can arise when this effort is required for a prolonged period.

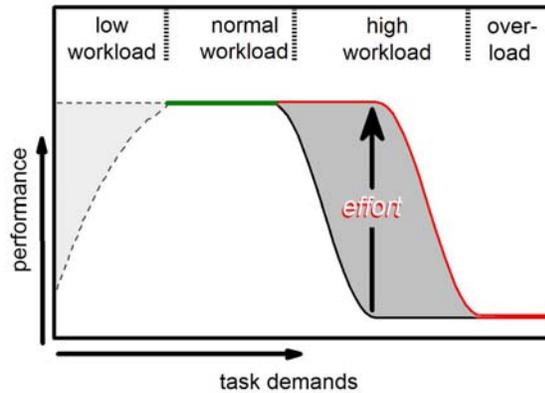


Figure 1. The relation between task demands, performance, and workload (from [27])

AC techniques describe various ways to estimate workload. According to Figure 1, we should measure performance, effort and task demands to get to an optimal mitigation strategy.

3.1 Operator Performance

The *operator's own performance* could be used as a trigger. Using the operator's interactions with the system allows us to determine performance measurement. Side-stepping the discussion on how to create a performance model, which remains difficult, this candidate allows to trigger adaptive behavior in order to optimize human-computer cooperation. For example, Geddes [28] and Rouse, Geddes & Curry [29] apply adaptive automation based on the operator's intentions predicted from patterns of activity. Though successful, performance modeling have been criticized as being too information sensitive, requiring a massive database of operator performance [30].

3.2 Physiological Measurements

Besides performance measures to determine the effort, (neuro)physiological data to understand the effort from the operator are used in various studies as well (e.g. [31] [32] [33]). Physiological measures can be recorded without respect to overt responses and provide an indication of cognitive activities. Specifically, pupillometry, heart rate variability [17], and electroencephalographs [34] have been studied and have yielded a reliable description of cognitive state. Differences in state were used as triggers and yielded reductions in effort and/or improvements in operator performance. Today, the brain based electroencephalographs [30] demonstrate a reliable engagement index from a ratio of EEG power bands that can be used for triggering mechanisms.

Various studies clearly demonstrate that physiological measures can measure the state of the operator. Although promising, there lingers one potential pitfall involving the usage of physiological measures to estimate effort. An operator continuously

adapts to changes in workload, and physiological reactions are a sign of this adaptive behavior. If a system uses this information to reduce the workload, there are two adaptive systems that might work counterproductive as is demonstrated by Wilson [35]. On the other hand, when one expects an increase in physiological indicators due to excessive task demands and this increase is not reflected in the physiological data, one could draw the conclusion with respect to the state of the operator (i.e., is the operator still in command of the situation).

3.3 Task demands

Another possibility to vary the levels of automation is to use the flow of the mission itself. Here, the occurrence of *critical events* can be used to change to a new level of automation. Critical events are defined as incidents that could endanger the goals of the mission. Scerbo [8] describes a model where the system continuously monitors the situation for the appearance of critical events and the occurrence of such an event triggers the reallocation of tasks. Inagaki [19] published a number of studies where a probabilistic model was used to decide who should have authority in the case of a critical event. Inagaki suggests that different time periods during the acceleration of an airplane for takeoff make it more or less important for automation to assume responsibility for a reject takeoff decision, should such a decision be required following an engine failure.

4 Cognitive Engineering for Adaptive Automation

Effective, efficient, and easy-to-learn operation support is crucial for joint human machine performance in complex task environments, such as ship control centers and process control rooms. An important aim of AC is to accommodate user characteristics, tasks, and contexts in order to provide the “right” information, services, and (support)functions at the *right* time and in the *right* way [36]. The previous sections provided an overview of both the opportunities and pitfalls of AC. Also different types of triggers were discussed including the difficulties that occur in identification, selection, and calibration of appropriate triggers. It turns out that due to the adaptive nature of both the human and machine, it is difficult to provide generic and detailed predictions on the overall human-machine performance at design time. Therefore, a new type of iterative methodology is needed that guides the development process. This method should enable us to address the mutual adaptation in an appropriate manner carefully weighing the costs and benefits at each iteration.

Cognitive engineering (CE) approaches originated in the 1980s to improve computer-supported task performance by increasing insight in the cognitive factors of human-machine interaction (e.g., [37] [38]). These approaches guide the iterative process of development in which an artefact is specified in detail, and specifications are regularly assessed to refine the specification. For adaptive systems, the “classical” methods have to be extended with an explicit technology input for two reasons. First, the technological design space sets a focus in the process of specification and generation of ideas. Second, the reciprocal effects of technology and human factors are made

explicit and are integrated in the development process. Also, the technology might not be mature at design time which prevents accurate performance predictions, an effect which is leveraged by the reciprocal effects. Finally, not a single mode of operation is chosen but a range of HMC modes. This range, its dynamics and triggers are guided by current and predicted technology. So, we propose a CE+ method, adding a technology perspective into common human factors (HF) engineering practices [39]. In addition to the added focus on the technology we propose to develop practical theories and methods that are *situated* in the domain. This is important to be able to assure an accurate weighing of costs and benefits within a specific domain while designing and developing adaptive systems.

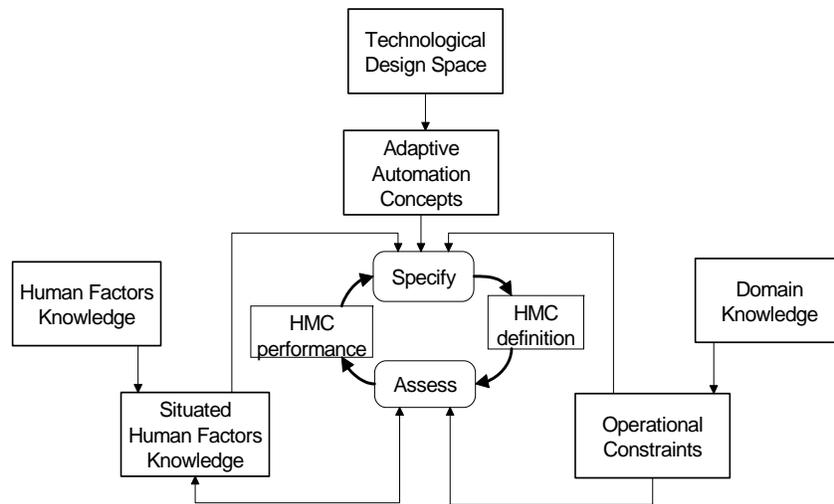


Figure 2. The situated CE+ method for optimizing human-machine co-operation using adaptive automation. The iteration stops if a suitable HMC definition is reached.

The situated CE+ method is shown in Figure 2. Generic human factors knowledge is contextualized into situated HF-knowledge (instantiated practical theories, guidelines, and methods for the specification and assessment). Adaptive automation concepts, triggers and ranges are derived from the technological design space. An analysis of the domain provides operational constraints. During HMC specification of the situated HF knowledge, the AC concepts and the operational constraints must be addressed concurrently resulting in a preliminary HMC definition. During the assessment it is checked whether the definition actually agrees with operational constraints and HF predictions. An assessment will provide qualitative or quantitative results in terms of effectiveness, efficiency, satisfaction, learnability, and trust which are used to refine, adjust or extend the specification. Eventually, the process of iteration stops when the assessment shows that the overall HMC system satisfies the requirements (as far as the resources and completion date allow). The situated CE+ framework has

been developed and applied for the design of cognitive support that augments the capacities of teams and team-members during critical and complex operations (e.g., to improve task load management, trouble-shooting and situation awareness). It is based on experiences with previous and current (space, navy) missions and based on practical theories on the object of support (e.g. cognitive task load [40]).

5 Conclusion

This paper reviews past and present research on the topic of the symbiotic relationship between man and machines, explaining the latest mitigation strategies, and finalizing with an iterative engineering methodology that takes into account the benefits and costs of the adaptation behavior of man and machine.

One way to make human-machine systems more effective and resilient is by dynamically engaging humans and machines in tasks. With augmented cognition it is the machine that adjusts the way activities are divided and shared between human and machine. Investigating ways to develop systems that reliably augment cognition in operational settings and allows one to cope with unreliability and knowledge about how humans use these systems should be high on the research agenda.

Although all three mitigation strategies for adaptive behavior have been proven successfully in experimental environments, they all have their pros and cons. To date, no studies have attempted to combine various triggers, and we strongly believe that combination of techniques prove very valuable [41] [42] and that the combining information might assist in resolving ambiguous situations.

The paper finalizes with the explanation of a framework for the design of cognitive support that augments the capacities of teams and team-members during critical and complex operations and we encourage people to utilize such a method in the designing process of augmented cognition systems.

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