The Evolution of Human Systems: A Brief Overview

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Abstract. Recently, there has been a profound resurgence interest in expanding the effectiveness of human machine systems. The motivation for this interest stems not only from the growing realization that better designed systems – tailored to augment their user's innate skills and capabilities – will enable users to 'do more', but also from the fact that the world with which we interact is becoming increasingly reliant on machines. In the past, the human machine interface was bridged through engineering based principles, but, with our expanding understanding of how the human brain drives behavior it is now possible to consider, as never before, human machine design efforts that fully address human and machine needs at the same time.

Keywords: Neuroscience, Cognition, Automation, Human Systems, Cognitive Model.

1 Introduction

Traditional approaches to creating human machine systems have focused on engineering or machine learning techniques to establish couplings between humans and their machines (Cooley, 2007). For example, many of the cognitive architectures that are intended to allow the machine to infer human intention are based on computer processing metaphors, not on actual brain dynamics. This is a direct result of the levels of technology available to understand and represent the processes through which the human brain transforms information into action. Until very recently, neither the imaging technologies nor the analytic capabilities were available to truly link actual brain activity to behavior. As a result, when one wished to create human machine systems one was forced to do so by basing this integration on observed behaviors, and building predictive models of human behavior on these observed behaviors.

Of course, the ideal is to directly link high fidelity representations of human behavior with machine operating systems. These representations may be found in the neural processes leading to the actual, observed behavior. Just as understanding the equations of motion provides a much broader set of capabilities than inferring these equations from a limited set of observations (Kelso, 1995), so too understanding and modeling the dynamics of neural activity as it leads to behavior should provide a much richer and more robust set of models than those based on the actual observed

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behavior alone. Today, advances in neuroscience and engineering provide the basis for building these 'equations of motion' for the brain and for using brain-based techniques to create and maintain very robust human machine interactions.

1.1 The Engineering Based Approach

The notion of creating human machine systems is not new. As early as the 1940s, researchers were concerned with the question of how to represent the human element in human machine systems. Using the engineering-based terminology of the time, Bates (1947), Craik (1947/1948; 1948) and others attempted to explain human performance in control theory terms with the goal of developing engineering representations of the human that could be used to improve human machine systems (Birmingham & Taylor, 1954). Others, like Chapanais (1951), applied a similar approach for analyzing human error in human machine systems.

In all cases, the properties of the human being modeled were only at the observed behavior level. For example, Fitts' speed-accuracy tradeoff (Fitts, 1954; Fitts & Peterson, 1964) emphasizes the development of basic relationships guiding human motor planning. Stevens' power law describes the relationship between the magnitude of a physical stimulus and its perceived intensity (Stevens, 1957), and the Hick-Hyman law relates decision response time to the number of possible choices (Hick, 1952; Hyman, 1953). One of the primary applications for this line of research was to develop more effective and responsive aviation systems (Adams, 1957; McRuer & Jex, 1967; Young, 1969). More broadly, fully automated systems which could perform tasks in the absence of actual human controller inputs were also envisioned as resulting from this line of research, as were human assistive systems (i.e. symbiotic systems, Licklider, 1960).

In one sense, automation may be thought of as a means of substituting human actions with those of a machine (Parsons, 1985; Parasuraman & Riley, 1997). The reasons for automating certain tasks range from safety considerations to cost and efficiency considerations (Weiner & Curry, 1980; Weiner, 1989). Inherent to the notion of automation is the idea that of an overall pool of tasks, some may be allocated to a system or machine, while others may be allocated to a human. In the most conservative sense (e.g. Licklider, 1960) automation requires a strict parsing of tasks – those at which a machine may excel and those at which a human may excel. Along those lines, Parasuraman, Sheridan & Wickens, (2000) proposed a set of discrete levels of automation to be implemented based on overall task context. Yet, as Rouse (1977) and Woods (1996) suggest, these kinds of approaches to automation are brittle. Situations change, information changes and people change, often as a consequence of using automation (Woods, 1996) and the allocation of tasks between humans and machines should be able to change, dynamically and in real time to provide the most effective assistance.

1.2 A Turning Point

The realization that dynamic changes in both users and their systems must be accounted for opened the door for a human-centered approach to human-systems design, leading to adaptive automation. Adaptive automation is an automation scheme that allows for control of tasks to be passed in real time, between human and machine – represents one attempt to bridge the human machine gap of classic automation (Scerbo, 1996). This kind of automation seeks to optimize human machine interactions by changing task demands in response to user performance. A direct result of this kind of automation is that the task environment is restructured, dynamically, in terms of *what* tasks are automated, *how* they are automated, and *when* they are automated (Rouse, Geddes, & Curry, 1988). A key consideration in adaptive automation is the means through which the adaptation is triggered. Early attempts at creating adaptive techniques focused on a purely artificial intelligence (AI) approach (Rouse, 1977), merging expert systems with knowledge based representations of human performance (or, loosely, cognition) to detect and assess task context, and develop adaptive strategies (e.g. Hammer & Small, 1995).

Yet, a significant disadvantage with this approach is that while representations of the human operator may be gleaned from psychometric measures (speed and accuracy types of measures), the level of fidelity of these representations is typically orders of magnitude less than that of representations of the system and task environment. Furthermore, the rate at which this information may be accumulated is similarly challenged. Human behavior typically evolves over a timescale measured in seconds, while machine action may occur over a millisecond to second timescale. In other words, currently available measures of the human are rate limiting in human-machine systems, even those that are adaptive.

1.3 Enter Neuroscience

Recent attempts to get around the human representation challenge have focused on adding another dimension of measurement, based on neurophsyiologically detected processes (Morrison & Gluckman, 1994). The basic premise is that by including neurophsyiological measures, it should be possible to gain higher levels of fidelity, over a shorter time course, for the kinds of human representation needed to make adaptive automation effective, beyond than simple observationally behavior based ones. These richer metrics would therefore serve as a more effective input into a dynamic and adaptive automation system (Scerbo, 1996). Such measures include (Scerbo, et al., 2001; Cohn, et al., 2005):

- Heart rate variability
- Eye-based responses (e.g. eye blinks, pupil diameter)
- Galvanic Skin Response
- Neural based signals (Electroencephalography –EEG, functional Magnetic Resonance Imaging – fMRI; functional Near Infrared imaging – fNIR)

These measurements provide a vast improvement over traditional measures that feed into adaptive automation developed to make use of them (e.g. Schmorrow, 2005; Schmorrow, Stanney & Reeves, 2007) and, collectively, have pushed the field of adaptive automation far ahead of where it might otherwise be. At the same time while these measures provide a more effective diagnostic metric indicating when automation might be useful, they don’t provide deeper descriptions of *what* tasks should be automated, *how* they should be automated, and *when* they must be automated. These determinations, in the current approach, are left to predefined strategies that are implemented based on the triggering of these measures (Rouse, et al., 1988).

2 Neuroadaptive Systems

The brain is not a static organ. It changes with experience (Cohn, Stripling & Kruse, 2005), creating new connections and optimizing older ones; it varies with emotional and physiological state, impacting and influencing higher order processes (Glimcher & Rustichini, 2004), and it is primed by changes in environmental context (Aamodt & Wang, 2008). The end result of the brain's inherent dynamicity is often changes in observed behavior (Cohn, Stripling & Kruse, 2005). Consequently, while it should be possible to create a closed loop human machine symbiotic system that can adapt its overall performance based on representations of brain activity care must be taken to understand precisely how to transform neural activity into representations of the behavior they encode.

Human Systems that incorporate elements of the brain's activity with representations of system state to enable human machine interactions are known as neuroadaptive systems. Neuroadaptive systems use the detailed output of their human users' neural activity in order to effectively adapt their behavior to the behavior of their users. This requires more than simply taking a snapshot of brain action. Neuroadaptive systems seek to enable adaptive interactions between humans and their machines using deeper and more representative measures of human neural action underlying behavior than those used in traditional adaptive automation technologies. With these representations, high fidelity individualized models of human performance can be crafted, which can be expected to behave in a manner analogous to that in which the human brain on which they are based will behave. Although still in their infancy, neuroadaptive systems are beginning to be realized as a direct result of recent advances in neuroscience and engineering.

2.1 Basis for Neuroadaptative Systems

Neuroadaptive systems are based on the idea that representations of the human user require the integration of measures across multiple levels, including brain based measures, cognitive measures and behavioral measures. This, in turn, requires advances in three core capabilities:

- Detection Technologies
- Decoding Methodologies
- Modeling Frameworks

2.2 Detection

The notion that human behavior is the result of coordinated activity across the brain is not new (Kelso, 1995). However, access to the brain has been one of the key limiting steps in demonstrating coordinated activity across the brain as behavior develops. As new technologies, like functional Magnetic Resonance Imaging (fMIR); (Logothetis, 2001), dense array Electroencephalography (dEEG); (Junghöfer, Elbert, Tucker, &

Rockstroh, 2000), and other types of tools become increasingly refined, simplified and incorporated into the researcher's toolkit, the ability to capture neural action simultaneously across multiple regions will continue to grow. As one example, Philiastides and Sajda, (2007) used an EEG based paradigm to illustrate the integration of different neural regions over time, as participants formed and acted upon a rapid decision making task.

2.3 Decoding

Access to integrated neural data is necessary but not sufficient for interpreting it in terms of cognitive processes. New processes for analyzing these multivariate data sets must also be established and refined, and efforts to do so have led to the development, refinement and application of these multivariate analytic techniques to data captured as participants perform a range of cognitive tasks. Briefly, multivariate decoding takes into account the full spatial pattern of brain activity, measured simultaneously across many regions, and enables the decoding of the current 'cognitive state' from measured brain activity (Haynes & Rees, 2006). Using this approach, it is possible to build classifiers that can distinguish between various cognitive behaviors, provided an adequate training set can be identified. Decoding routines have recently been applied to accurately decode meaning (i.e. simple thoughts) from neural activity (Mitchell, 2004; Mitchell, 2008).

2.4 Modeling

Perhaps the greatest challenges still remain in the domain of modeling - developing cognitive models based on how information flows, and is processed, across the brain, to simulate what the content of cognition will look like, based on neural activity. One approach that continues to gain momentum is to take existing cognitive models and link them to neural data. For example one of the better known cognitive modeling approaches is ACT-R (Anderson, 1996). ACT-R is an implementable theory of how human cognition works, based on the underlying assumption that knowledge is encoded from the environment and synthesized into 'cognition,' leading to behavior. Within the ACT-R framework, modules and buffers represent knowledge and processing of that knowledge, with cognition emerging through their activation. In its executable form, the timing and sequencing of model components is based on observed behaviors, and the output is typically timing and accuracy predictions.

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