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Enhancing the effectiveness of human-robot teaming with a closed-loop system

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ABSTRACT

With technological developments in robotics and their increasing deployment, human-robot teams are set to be a mainstay in the future. To develop robots that possess teaming capabilities, such as being able to communicate implicitly, the present study implemented a closed-loop system. This system enabled the robot to provide adaptive aid without the need for explicit commands from the human teammate, through the use of multiple physiological workload measures. Such measures of workload vary in sensitivity and there is large inter-individual variability in physiological responses to imposed taskload. Workload models enacted via closed-loop system should accommodate such individual variability. The present research investigated the effects of the adaptive robot aid vs. imposed aid on performance and workload. Results showed that adaptive robot aid driven by an individualized workload model for physiological response resulted in greater improvements in performance compared to aid that was simply imposed by the system.

1. Introduction

The population of robots in the world reached 8.6 million in 2010 (Guizzo, 2010). In 2016, the global robotics market was worth $25.9 billion USD. This is expected to reach $31.5 billion USD in 2021, expanding at a compound annual growth rate of 4.0% (Wilson, 2016). Although traditionally robots have been assigned tasks that are typically “dirty, dangerous, and dull” (Takayama et al., 2008), in recent years, increased robot functionality has resulted in their deployment in a greater variety of domains such as in bomb disposal, search and rescue missions, manufacturing (Guizzo and Ackerman, 2012), as surgical robots in healthcare (da Vinci surgery, 2013), and as robot assistants for the elderly or disabled (Kumar et al., 2006) in which their more intelligent contributions are now being mandated.

Despite these advances, robots are still largely teleoperated via remote control and require explicit commands, which confines their use to relatively structured tasks. To enable robots to operate in more novel environments, performing less structured tasks, robots must be capable of richer human-robot communications that may approach that exhibited in human teams (DRC, 2013). Robots with such capability should be more responsive to humans and exhibit behaviors that approximate teaming, including sensing the human operator's psychological status such as experienced workload and fatigue. One possible strategy for enhancing capability is through the use of a closed-loop system that adapts the robot to provide appropriate support when the human becomes overloaded (see Hancock and Chignell, 1988).

1.1. New technology for human-robot communication

A closed-loop system uses feedback or error signals to drive corrective actions that maintain a desired system state (homeostasis). Such systems have been in existence for several centuries, with many modern examples (e.g., thermostats, cruise control in cars). However their use in the human-robot teaming context is relatively recent. A closed, feedback loop, using measures of the human operator's workload as input, could allow selection of robot aiding behaviors that maintain the operator's workload state at a moderate target level (see Hancock and Chignell, 1987). Hence, if the operator is experiencing high workload to the point that

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jeopardizes his/her performance, the robot can aid by relieving the operator of certain tasks. Robot teammates' behavioral repertoire can include aiding with subtasks without being instructed to do so, such as anticipating needs by appropriately escalating information, and initiating actions such as messaging for help instead of requiring the operator to do so him/herself. When operator workload state returns to more manageable levels, the robot can adapt its behaviors to return full task control to the human teammate. Adaptive reversion of task control to the human teammate may minimize the often-cited problems associated with having the human "out-of-the-loop" such as the loss of situational or system awareness, increased complacency, over-reliance issues, skill atrophy, performance degradations, and unbalanced mental workload (Carmody and Gluckman, 1993; Endsley and Kiris, 1995; Parasuraman and Wickens, 2008; Smith and Hancock, 1995).

Critically, the robot must be capable of detecting this human overload implicitly, without overt instructions. Implicit communications is crucial where the operator is unable to issue explicit instructions. For instance, the operator may be experiencing such high workload but task demands prevent him or her from being able to instruct the robot on how to assist. It is also possible that operators may not be aware of their own workload state when intensely engaged in the task at hand.

The closed-loop system therefore requires a workload model that assesses and classifies operator workload without operator input. Subjective workload responses tend to disrupt performance as they require the operators' explicit reports. In contrast, physiological measures of workload allow continuous assessment, provide high temporal resolution, and rarely require any disruptive overt response from the operator. Thus, they are particularly suitable as indicators of operator workload in adaptive systems (Byrne and Parasuraman, 1996; Hancock and Chignell, 1987, 1988). Despite these advantages, physiological assessments also have limitations (Cain, 2007). Depending on the measure, these may include lower sensitivity to task demands relative to subjective scales, or sensitivity to certain characteristics of taskload only. Measures may also be contaminated by general stress responses. Conceptual linkages from physiology to performance may also be insufficiently specified. Nevertheless, developments in recording and processing physiological signals, together with accumulating evidence for validity, have heightened interest in the physiological approach (e.g., Chen and Barnes, 2014).

The basis of physiological workload measures (e.g., heart-rate, ocular activity, brain activity, hemodynamics) lies in the notion that, with the activation of various cognitive processes required to process task demands and execute the required responses, there are correspondng physiological responses. Commonly-used measures include heart rate, heart rate variability, respiration rate, brain activity, pupil size (diameter), and electrodermal activity, among many others. Rationales for specific measures may be found in reviews by Abich (2013), Borghini et al. (2014), Warm et al. (2012), Meshkati et al. (1995), and Young et al. (2015). For the present study, the physiological workload measures selected address responses in both central (i.e., brain activity, cerebral perfusion as indicated by level of oxygen saturation, and cerebral bloodflow velocity) and peripheral responses (i.e., cardiac and ocular responses) that index such cognitive activity.

1.2. Development of a workload model that accommodates individual variability in physiological responses

A challenge for ergonomic applications is the complexity of the neuropsychological workload construct (e.g., Young et al., 2015). Different metrics for workload may dissociate from one another, and from performance as task demands change (Hancock and Scallen, 1996; Horrey et al., 2009; Szalma and Teo, 2012). In the adaptive aiding context, it is essential to distinguish (1) objective external task demands (which we call "taskload"), (2) objective performance, and (3) workload as subjective and physiological indicators reflective of operator neurocognitive state. In some circumstances, loss of performance may be used to drive an automated aid directly, without the need for workload assessment. By contrast, use of workload rather than performance as the driver may be more effective in contexts in which (1) it is difficult to monitor performance continuously, (2) performance is influenced by multiple factors, and/or (3) it is important to anticipate future performance degradation as initial compensation for high task load becomes increasingly difficult (Cain, 2007; Hancock and Warm, 1989).

However, workload-driven adaptive aiding will only be effective if there is a negative taskload – performance association, so that mitigating taskload enhances performance. There are several circumstances in which taskload dissociates from performance. At moderate levels of demand, people often compensate for changing taskload levels to maintain constant performance, although low workload appears to be especially hard to manage (Hancock and Warm, 1989; Saxby et al., 2013) and may contribute to loss of situation awareness (Young and Stanton, 2007). Indeed, workload may reflect the operator's strategies for active management of task demands, strategies that may change dynamically during the course of performance (Hockey, 1997; Saxby et al., 2013). Especially in real-life settings, high workload may be experienced as enjoyably challenging and motivating (Matthews, 2016), potentially leading to positive workload-performance associations (Abich et al., 2017). Thus, workload is primarily useful for driving aiding or other automation in task settings that produce congruent reactions indicative of overload: subjective workload and stress, little strategic compensation, and performance impairment.

Even within the subset of task environments in which workload is diagnostic of performance, there are assessment challenges, e.g., different workload measures do not always concur. Workload may be assessed with subjective scales such as the NASA-TLX (Hart and Staveland, 1988), but such measures do not adequately capture physiological response (Matthews et al., 2015). Different forms of taskload, such as working memory demands, multi-tasking, and signal salience may all provoke feelings of overload. However, different taskload factors may elicit different patterns of physiological responses so that an algorithm based on responses to increasing working memory demands, for example, might not be effective in driving an adaptive system for handling multi-tasking.

A further major challenge associated with the use of physiological workload measures involves the large inter-individual variability of such responses (e.g. Hancock et al., 1985; Moray, 1984; Meshkati and Loewenthal, 1988; Roscoe, 1993; Johannes and Gaillard, 2014). There are multiple, weakly-correlated workload responses associated with indices of autonomic and central nervous sytem functioning. For example, one individual might show a strong electroencephalographic (EEG) response but a weak electrocardiac response, whereas another person might show the opposite pattern (Matthews et al., 2015). The workload model driving the closed-loop system would need to accommodate this inter-individual variability in physiological responses to workload across multiple measures in order to be fully effective.

The present study used a task environment represented by a simulation of an unmanned vehicle operation. This met the criteria we have defined for application of workload-driven adaptive aiding. The participant monitored one or more computer-screen windows for critical signals. The task imposed relatively high event rates to make the task attentionally demanding and limit possible strategic compensation. Taskloads are not so low as to