Robot Behavior for Enhanced Human Performance and Workload

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Abstract. Advancements in technology in the field of robotics have made it necessary to determine integration and use for these in civilian tasks and military missions. Currently, literature is limited on robot employment in tasks and missions, and few taxonomies exist that guide understanding of robot functionality. As robots acquire more capabilities and functions, they will likely be working more closely with humans in human-robot teams. In order to better utilize and design robots that enhance performance in such teams, a better understanding of what robots can do and the impact of these behaviors on the human operator/teammate is needed.

Keywords: Human-robot teaming, Robot behavior, Performance, Workload.

1 Introduction

In recent years, robots have been deployed in more areas than before. Although robots are used for a variety of reasons ranging from being able to perform tasks that are impossible for humans to accomplish, undertaking tasks that endanger human lives, and being more cost effective to deploy, one of the most often-cited reason for their use is that they can enhance human performance and relieve workload.

2 Robots in Context

2.1 Military

The military uses robots to carry out tasks that are too difficult or dangerous for soldiers. For instance, *Daksh* is a teleoperated military robot that clears improvised explosive devices. It can maneuver in various environments, including climbing stairs, and has an X-ray device on board to scan objects. The *MARCbot* is a military robot that inspects suspicious objects. It has a camera that is elevated in a post that enables it to look behind doors. It can operate for 6 hours on a full battery charge and soldiers have used it in the Iraq to detect hazardous objects. On the other hand, the *Goalkeeper* from the Netherlands helps defend military assets by tracking incoming missiles with its autocannon and advanced radar in its close-in weapons system. Another robot with

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a similar defence function is the *Guardium*, an Israeli unmanned security robot that guards and attacks any trespassers with its lethal and less-lethal weaponry. The *PackBot* series is a set of robots that can be fitted with particular kits that allow them to perform various tasks ranging from identifying, disarming and disposing IEDs, to detecting snipers through localizing gunshots from azimuth, elevation and range, to collecting air samples in order to detect chemical and radiological agents. *PackBots* were the first robots deployed to the Fukushima nuclear disaster site. Likewise, the *TALON* robots are used for a variety of tasks depending on the sensor or weapon modules that they are fitted with. They were used in Bosnia to safely remove and dispose of live grenades, and deployed in search and recovery missions, such as that in Ground Zero after the September 11 attack on the World Trade Center ("Current Use of Military Robots," 2014).

2.2 Healthcare

Robots have also been used in the medical field. With the *da Vinci* surgical assistant robot, surgeons have performed minimally invasive delicate surgeries with the help of its high-definition 3D vision system and robot arms with "wrists" that are able to make smaller, more precise movements because they bend and rotate far more than the human wrist. To date, the *da Vinci* has helped with approximately 1.5 million various surgical procedures worldwide (da Vinci Surgery, 2013). On the other hand, other robots make surgeries unnecessary. The *Magnetic Microbots*, developed in Switzerland, are each about the width of a strand of human hair. They are maneuvered and controlled with great precision by a series of electromagnetic coils, and have been used to treat a type of blindness that traditionally requires surgery (Liszewski, 2013). *Magnetic Microbots* have also been used to remove plaque from patients' arteries, as well as in disease screening, and in the treatment of cancer (Martel, 2012). Another robot that is used directly in therapy is the *Walk Training Assist* robot developed by *Toyota*. Attached to the patient's paralyzed leg, it helps patients walk and balance through a number of motion detectors and supports the patient as he moves to walk. On the contrary, other robots in healthcare are "service robots" that perform tasks of caregivers. For example, the *Bestic Arm* robot is fitted with a spoon on the end and helps patients who are unable to move their arms or hands to eat without requiring help, and the *Aethon TUG* and *RobotCourier* are both robots that move through hospital corridors, elevators and wards to deliver medication on schedule, or lab results and bed linen. There are claims that they are able to do the work of three full-time hospital staff, and yet cost less than one. Other robots like the *Vasteras Giraff* are equipped with a camera, a monitor, and a two-way video call system that enable doctors in hospitals to monitor and communicate with their elderly patients at home. In contrast, the *CosmoBot*, is used in therapy for developmentally disabled children. *CosmoBot's* cartoon-like appearance helps the child patient to warm up to it so that it is able to collect data on the child's performance, allowing the therapist to evaluate progress. (McNickle, 2013).

2.3 Manufacturing/Domestic Applications

In the manufacturing industry, robots boost productivity, as they are able to manipulate materials and objects in assembly lines with great precision and speed. Australia's *Drake Trailers* saw a 60% increase in productivity due to the inclusion of a welding robot (ABB Australia, 2010), and the *Unimate* robot, that is used to pour liquid metal into die casts and weld auto bodies, has improved processes in the manufacture of automobiles at General Motors (Lamb, 2010). Another robot that performs mechanical tasks with high precision and speed is the *Selective Compliance Assembly Robot Arm or Selective Compliance Articulated Robot Arm (SCARA)*, which has "arm" joints that enable it to move deftly in and out of confined spaces to install delicate and tiny components (Kuka, 2013). More recently, in addition to performing different repetitive tasks, industrial robots have developed to work more closely with humans. For instance, *Baxter* the robot is a human sized, two-armed robot with an animated face. Unlike its predecessors, it does not come pre-loaded with programs that direct it to operate. Instead, through a series of prompts, the robot can be "taught" to perform certain tasks by moving its arms in the desired motion and having it "memorize" the movements. Equipped with a range of cameras and sensors, *Baxter* also has a degree of "behavior-based common sense" and is capable of sensing and adapting to its task and environment (Guizzo & Ackerman, 2012).

Robots are also used as domestic help both indoors and outdoors. The *Roomba*, vacuums the carpet, while the *iRobot Scooba 230* washes the floor. Both are able to navigate around the house and are relatively small in size, allowing them to clean in tight spaces and under furniture. Outdoor robots like the *LawnBott LB3510* and *Husqvarna Automower 230 ACX* are able to mow uneven lawns and at an incline, and the latter is also equipped with an antitheft alarm (Swan Robotics, 2014). Others, like *Jazz Security*, are security robots that are outfitted with night-vision capable wide-angle cameras that shoot videos and sensors that detect motion on the grounds. The robots would also alert the house owner of activities on the suspicious activity on the property. This concept of patrolling has been extended to telepresence. The *Jazz Connect* is a robot that can be stationed at home while its operator is away. It allows the operator to move around the house and communicate with the people present as though he/she were at home. This application permits caregivers to check on their stay-in patients or parents to check on their children while at work (Aki, 2012).

2.4 Entertainment

Robots have also been developed for recreational purposes. They may take the form of a pet, like a dog (e.g. *Poo-Chi* or *Aibo*), or guinea pig (e.g. *Gupi*). Some are interactive and can perform various tasks and tricks on command like *Teksta*, the robot dog that does backflips and wags its tail when its name is called, expresses emotions through its eyes, and responds to touch. Other robots serve as art pieces and installations (Bubblews, 2013). For instance, *Paparazzi Bots* were developed as a statement against modern culture's obsession with images of ourselves and celebrities. The robots, which are about the height of a human and move at human speed, are outfitted with a range of cameras, actuators and sensors, and behave like paparazzi, moving among people capturing photographs of people and making them accessible to the world (Rinaldo, n.d.). Furthermore, there is *ARTI,* an interactive robot driven by artificial intelligence that functions like a museum curator as well as exhibit. It is capable of recognizing faces and understanding speech, and teaches museum guests about the history and exhibits of the Intel Museum (West, 2008).

In all these applications, robots display a variety of behaviors, befitting of their intended function. However, it is important to understand how these behaviors affect the human, particularly in enhancing performance and reducing workload and stress. This calls for an understanding of the stages involved in information processing and performing tasks.

3 Relating Robot Behaviors to Human Information Processing

In the attempt to understand how automation may help enhance performance and reduce workload, Parasuraman, Sheridan and Wickens (2000), proposed that automation can support the human in four primary areas: (i) information acquisition, (ii) information analysis, (iii) decision selection, and (iv) action implementation. This classification of tasks was based on a simple four-stage model of human information processing (Parasuraman et al., 2000).

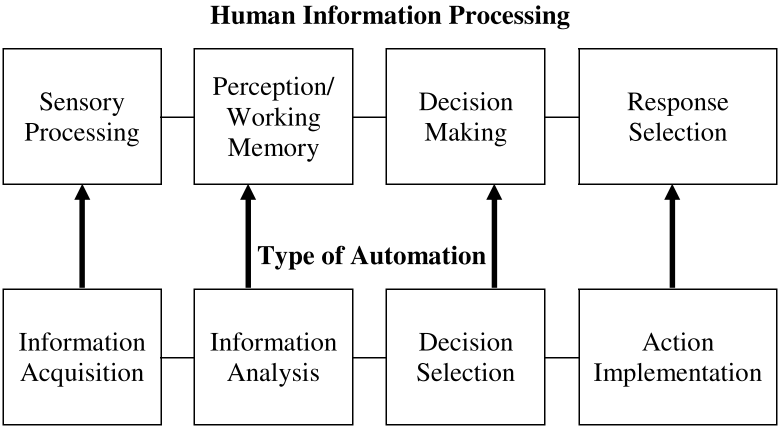

Fig. 1. Simple four-stage model of human information processing and types of automation. Adapted from Parasuraman, Sheridan, and Wickens (2000).

The framework provides a way to classify factors and dimensions that impact performance and workload in both human-computer and human-robot systems For example, researchers have identified taxonomic elements that contribute to usability and user satisfaction in human-computer systems that include interface design, input/output devices, learnability, perceptual factors, memory load required, and perceived usefulness (e.g. Çalişir & Çalişir, 2004). Likewise, from reviewing multiple studies, Prewett et al. (2010) proposed several guiding principles and propositions for reducing operator workload in human-robot interaction. These include the type of visual display, number of multimodal displays/cues, amount of system delay, and environmental complexity, and can be traced to the cognitive processes they affect, attesting to the value of such a framework. In addition, a taxonomy of human-robot interaction proposed by Yanco and Drury (2002; 2004) included factors that relate more to the task at hand, as well as factors that drive the human-robot interaction. Their list comprised task type, task criticality, robot form/morphology, ratio of humans to robot, composition of robot teams, level of shared interaction among teams, interaction roles, type of physical interaction between human and robot, decision support for operators, time/space relationship between human and robot, and level of autonomy of robot.

These factors and taxonomic dimensions can be mapped onto the information processing stages that they impact. For instance, number of displays, camera type, lags in system visual image processing mostly affects information acquisition, while the number of robots controlled and ratio of humans to robots impact more information processing stages, and potentially have more influence on workload, performance and stress. Such an approach to understanding robot behaviors would enable developers of automation to understand the human cognitive processes that their automation supports, and how the automation affects performance and workload. This would facilitate development of robots that work and collaborate better with humans, thereby increasing the possibility that robots would be able to team effectively with humans in the near future.

4 Next Generation Robots: Robots That Team with Humans

In 2013, the Defense Advances Research Projects Agency (DARPA) acknowledged that presently, robots operate mostly in controlled and well-defined environments, doing simple, repetitive tasks as they require too many step-by-step commands. To be effective in the unpredictable real world, the robots of the future should operate in novel situations without requiring extensive reprogramming and should still be able to operate even when communications with the human are delayed or interrupted. This entails robots having “task-level” autonomy, as opposed to being teleoperated (DRC, 2013). Such capabilities would also render robots more able to work more closely and team with humans. This vision of robots was also echoed in a recent announcement that the National Science Foundation (NSF), in partnership with the National Institutes of Health (NIH), U.S. Department of Agriculture (USDA) and the National Aeronautics and Space Administration (NASA), has made new investments totaling approximately $38 million for the development and use of robots that are able to work collaboratively with humans to enhance human capabilities, performance, and safety (R&D, 2013).

If human-robot teaming is to be the goal in the coming decades, then understanding the influence of robots on humans is imperative. In developing a framework for robot behaviors in human-robot teams, we draw upon theories from team research, including theories of team roles and social support.

5 Review of Related Team Research

5.1 Team Roles and Functions/Behavior

A team differs from a social group in that all teams are formed to achieve certain goals or to perform a task. Belbin (2013) proposed that teams can be more productive, high-performing, and team members can be more self-aware and personally effective when there is an understanding of the strengths and weaknesses of each member. He proposed that there are nine team roles, and each fall into one of three categories; (i) action-oriented roles, (ii) people-oriented roles, and (iii) thought-oriented roles. Under the action-oriented roles, there is the *Shaper*, who challenges the team to improve and move forward, the *Implementer*, who puts ideas into action and is well-organized, and the *Completer/Finisher*, who works to ensure that the team completes the task in a thorough, timely manner. The people-oriented roles include the *Coordinator*, who acts as a chairperson, delegating and clarifying goals, and promoting decision-making, the *Team Worker,* who, being a good listener, works to resolve social problems and encourages cooperation, and the *Resource Investigator*, who explores outside opportunities and develops contacts that can help the project. Under the thought-oriented roles, there is the *Plant*, who presents new ideas and approaches, the *Monitor-Evaluator*, who analyzes the options, and the *Specialist*, who provides specialized skills (Belbin, 1981; 2013).

Some team roles (i.e. action-oriented roles) serve to move the team towards achieving its goals, while other roles are more focused on fostering relationships and communication that facilitates goal-attainment (i.e. people-oriented roles). On the other hand, some team roles that encourage the team to generate new ideas, self-evaluate, and examine its strategy and approach in reaching the goals (i.e. thought-oriented roles).

The main concept behind the various team roles is that there are different sets of behaviors found in an effective team (Belbin, 1981; 2013). Behaviors may pertain directly to the task/goal (e.g. clarifying goals or generating new ideas) or indirectly to the task/goal (e.g. communicative and self-evaluate behaviors).

5.2 Types of Support

Apart from team roles, there are theories that address various types of help or support behaviors. House (1981) postulates that there are four basic types of support that members of a social network may offer each other: (i) informational support, (ii) instrumental support, (iii) emotional support, and (iv) appraisal support. Informational support refers to the provision of suggestions and information that the individual in need can use to address the problem faced, while instrumental support involves the giving of tangible aid and services that directly help the individual in need. On the other hand, emotional support refers to the sharing of emotions and provision of empathy, love and caring, while appraisal support refers to the provision of constructive feedback and affirmation for the individual's self-evaluation. These four types of support may broadly be classified as (i) direct, and (ii) indirect support. Informational and instrumental support pertain directly to need or problem encountered, while emotional and appraisal support may help the individual cope of the problem better, but do not address the problem directly.

Applying this notion to a human-robot team, it is then possible to conceptualize potential robot behaviors as being directly or indirectly aiding the human.

5.3 Structure in Teams

Drawing on the language of management and industrial psychology, automation and HCI researchers have proposed theories that incorporate the relationships and roles of supervisor, peer and subordinate. In his work on automation, Sheridan (1992) describes five generic supervisory functions that comprise planning the task, programming the computer, monitoring the automation's actions to detect failure, intervening with a new goal or taking over control in the event of failure, and learning from experience. Furthermore, a theory of human-robot interaction proposed by Scholtz (2003) outlines several relationship and roles that may be found in human-robot teams. These roles, based on Norman's stages of HCI interaction (Norman, 1986), include the (i) supervisor, (ii) operator, (iii) mechanic, (iv) peer, and (v) bystander, and differ in terms of the level of involvement of the human and the autonomy of the robot. The theory acknowledges that the different roles are associated with various levels of autonomy, for instance, the supervisor has more autonomy and operates at a higher goal level than the peer role. This is similar to that in human teams, where the supervisor typically has more autonomy than the peer, who has more autonomy than a subordinate does.

5.4 Gradations of Autonomy

Despite their benefits, there are some detrimental effects of automation on human performance. These include problems such as complacency, decreased vigilance and loss of situation awareness (Endsley, 1987; Carmody & Gluckman 1993; Parasuraman et al., 1993; Endsley & Kiris, 1995; Parasuraman & Riley, 1997). Researchers describe the underlying problem as having the human out-of-the-loop (OOTL) (Young 1969; Kessel & Wickens, 1982). To address this, strategies to manage the use of automation have been suggested. These broadly fall under the levels of automation approach and the adaptive automation approach. Billings (1997) proposed two approaches to automation, while Sheridan and Verplank (1978) described more explicit levels of automation. Adaptive automation, on the other hand, has been studied by researchers such as Rouse (1977; 1988), Parasuraman, Mouloua and Molloy (e.g. 1996), among others.

Management-by-Exception and Management-By-Consent. Billings (1997) proposed two approaches to use automation in aviation: management-by-consent and management-by-exception. Management-by-consent occurs when automation only takes action when explicit consent has been obtained by the operator to do so, whereas when the management-by-exception strategy is adopted, automation is able to initiate and execute actions without explicit consent from the operator, who retains the option to override or reverse the actions taken or initiated.

Levels of Automation. Another theory incorporating the similar idea of gradations of automation is Sheridan and Verplank's (1978) levels of automation (LOA). The theory involves a scale with ten degrees or levels at which automation can aid with decision and action. Higher LOA represent increased machine autonomy while lower LOA denote greater human involvement and diminished automation (Parasuraman et al., 2000). For instance, operating at high LOA in the information acquisition stage may provide the operator "decluttered" and filtered information already categorized according to certain criteria such that the "raw" data is unavailable to the operator (Yeh & Wickens, 2001). On the other hand, medium LOA in the same stage only tentatively classifies incoming data, allowing the operator to see the "raw" data (Parasuraman et al., 2000). In the information analysis stage, lower LOA merely provide a simple trend lines, providing only minimal support with regard to the evaluation of the information. The main concept of LOA is to automate the system only to a moderate degree to minimize the problems associated with excessive automation.

Incorporating this concept of levels of automation, Save & Feuerberg (2012) further developed the four-stage model of information processing to include gradations within each stage that reflect the degree to which automation was involved. For instance within the decision selection stage, the level of automation can range from being fully human-driven ("human decision making") to fully automated ("automatic decision-making"), with intermediate levels such as "artifact-supported decision making", "automated decision support", "rigid automated decision support", "low-level automatic decision-making", and "high-level automatic decision making".

Adaptive Automation. In addition to having multiple levels of automation, or, in the case of a human-robot teams, multiple levels of robot autonomy, there can also be a customization of the robot's level of autonomy to the changing needs of the human teammate. In automation research, this is the concept of adaptive automation (AA) (Rouse, 1988). While LOA identifies the degree to which automation is implemented, AA pertains to when the different levels of automation are invoked (Taylor, Reinerman-Jones, Szalma, Mouloua, & Hancock, 2013).

The effectiveness of the AA strategy has been observed empirically (Rouse, 1977). For instance the adaptive automation scheme where the automated tool was only used during high traffic conditions, resulted in the smallest increase in mental workload among Air Traffic Controllers compared to the constant automation and constant manual schemes (Hilburn, Jorna, Byrne & Parasuraman, 1997). Parasuraman et al. (1996; 1993) found that adaptive automation improved detection of system failures in a multitask flight simulation. In addition, adaptive automation was found to improve performance especially when the type of automation was matched to the type of task demand (Taylor et al., 2013).

Incorporating these theories and ideas in a human-robot team, it is proposed that the level of autonomy of the robot can be managed in terms of the roles that it assumes. In most situations, the robot would be a subordinate, having limited autonomy, as reflected by the set of behaviors that it can exhibit. These behaviors are likely to be "passive" and are responses to explicit commands. However, applying the AA idea, under certain circumstances, it may assume a role with greater autonomy, such as that of a peer, which entails a set of more "active" behaviors that are associated with greater autonomy and initiative.

6 Dimensions of Robot Behaviors

Drawing from the various related theories and literature, robot behaviors can then be (i) active or passive, corresponding to different levels of autonomy, as well as (ii) impacting performance, workload and stress directly or indirectly. Table 1 shows some examples of behaviors in each category:

Table 1. Taxonomy of robot behaviors

	DIRECT	INDIRECT
ACTIVE	**Robot shows affirmative behaviors that aid with operator's main task.** Example behaviors: • Takes over operator's task entirely. • Aids operator with his task by taking over parts of the main task. • Aids by preventing others' inputs from hindering operator from main task.	**Robot shows affirmative behaviors that aid with operator's secondary tasks or indirectly helps with the main task.** Example behaviors: • Aids operator with his main task by reminding him (indirect help) of certain aspects of the task. • Aids operator by relieving him of secondary tasks. • Aids by preventing others' inputs from hindering operator from secondary tasks.
PASSIVE	**Robot helps by withdrawing its own inputs from hindering the operator from his main task.** Example behaviors: • Stops feeding inputs that may disrupt operator from main task.	**Robot helps by withdrawing its own inputs from hindering the operator from his secondary tasks.** Example behaviors: • Stops feeding inputs that may disrupt operator from secondary tasks.

Hence, with a human-robot team, in line with the levels of automation/autonomy notion, there should be different roles and correspondingly, different sets of behavior that the robot can exhibit. This will help minimize issues associated with having the human out-of-the-loop. Additionally, applying the idea of adaptive automation/autonomy, the robot should be able to assume different roles and the associated behavior sets depending on the workload and stress experienced by its human teammate.

7 Conclusion

The field of human-robot teaming is a relative new but a promising one. Although development of robots and programming of their behaviors are usually first driven by functional specifications, the resultant product may or may not meet intended functions because in human-robot teams, it is the interface and interactions that are key. Hence, much research and a multi-disciplinary approach is required to develop robots that can be shown to enhance human performance while mitigating workload and stress.

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