CHAPTER 4

Principles of Human-Machine Interfaces and Interactions

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This chapter introduces basic principles of human-machine interfaces and human-machine interactions, including issues of levels of autonomy, teaming, human performance enhancement, and shared control between machine and human operator. Specific challenges that face life sciences and micro-nano applications are given.

4.1 Introduction

Human-machine interaction (HMI) can be generally defined by drawing upon related literature on human-computer interaction (HCI) and human-robot interaction (HRI). Indeed, the body of research on HCI is much broader than that for HRI or HMI individually, and current challenges in HCI can be extended and applied to human-machine interactions for discussion as it applies to life science automation.

The discipline of HCI is generally considered to address the design, evaluation, and implementation of human-operated interactive computing systems, and the study of related topics concerning such systems. In this context, there can be multiple humans and/or machines considered. The Association for Computing Machinery's (ACM) Special Interest Group on Computer-Human Interaction (SIGCHI) lists several areas of primary study, including joint performance of tasks by humans and machines, communication structures between entities, capabilities of humans to use and learn to use such machines, interface design and fabrication concerns, specification, design, and implementation processes, and design trade-offs. Given this broad range of topics which are of concern to researchers in the field, there are clearly multiple relevant disciplines involved in HCI research, including computer science, psychology, sociology and anthropology, and industrial design.

HRI specifies the computer as a robotic device, and the majority of the field deals with industrial robots, mobile robots, or personal or professional service robots [1]. When we shift away from the terminology "human-computer" interface and seek to specify the human-robot or human-machine interface, the manifestation of the machine (as opposed to software) brings into the fold the engineer. In turn, the designer of such interfaces must consider the additional aspects of machine

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design, ergonomics, safety, interaction modality, and other concerns. HRI is typically distinguished from HCI and HMI in that it concerns systems with complex, dynamic control systems, systems that exhibit autonomy and cognition, and which operate in changing, real-world environments [2]. When considering the principles of human-machine interaction as they apply to life science automation, we note the absence (typically) of interaction with systems that exhibit cognition. Also, systems for the life sciences are typically operating in controlled, laboratory environments, thus further distinguishing HMI from HRI. The remainder of this chapter will focus only on those relevant aspects of human-machine interaction and human-machine interfaces that are pertinent to life science automation, and will specifically omit discussion of cognitive architectures in human-robot interaction and mobile robotic systems.

4.2 Fundamentals of Human-Machine Interaction

There are four primary elements of all human-machine interfaces, as summarized by Degani and Heymann [3]. These include the machine's behavior, the operational goals or task specification, the model that user has about the machine's behavior (referred to as the user model), and the user interface (through which the user obtains information about the machine's state and responses). They state that these four elements must be suitably matched in order to insure correct and reliable user-machine interaction. Their work describes an evaluation methodology to determine if an interface provides to the human sufficient information about the machine so that the task can be successfully and unambiguously completed. In order to carry out such evaluation, a set of assumptions are made including the existence of an underlying model of machine behavior, machine behavior that is unambiguous and deterministic, specified operational requirements for the system, and formal representation of the user model gleaned through training materials and documentation.

Human-machine interfaces can be problematic, as summarized by Woods et al. [4]. Specifically, the interface to operator may provide inadequate information about the current state of the machine, there may be perplexing interactions among machine components that are not clear to the operator, and the operator may have an incomplete user model of the machine's behavior. These problems may limit the operator's ability to anticipate future behavior of the machine, leading to confusion on the part of the operator, and the potential for errors [3].

Hoc provides a discussion of failures in human-machine systems and focuses on four primary types of failure that result from both the design of the interface, and the cooperation between man and machine [5]. Specifically cited are loss of expertise, complacency, trust and self-confidence, and loss of adaptability. Loss of expertise is often attributed to the operator taking a passive role [6] and is a clear trade-off when low-level functions such as decision implementation, or high-level functions such as decision making are automated [7]. Complacency arises when automation performs high level functions, and operators take solutions presented by automation systems for granted and without question [5]. When an operator can choose between manual or automatic operation of a system, trust and self-confidence in the machine are an important factor in the utilization of the automation [8–10]. Finally, loss of adaptability of the human-machine system, primarily due to limited feedback to the human operator during automated decision making, leads to a syndrome of human out of the loop and makes it difficult for the operator to regain manual control of the system [11, 12].

With these definitions of human-machine interactions in mind, the remainder of this section will provide a brief introduction to the categories of robotics and machines used in life science automation. In addition, some background on design of automation systems, performance measures, human-machine teaming, and communication between humans and machines is presented.

4.2.1 Robotics and Machines for Life Science Automation

Using the categories of robotics given in the introduction (industrial robotics, professional service robotics, and personal service robotics), we can discuss scenarios that are relevant to life science automation. Typically, an industrial robot is considered to have three elements: manipulation of the physical environment (pick and place), computer control, and operation in industrial (controlled) settings [1]. It is reasonable to extrapolate these elements to a life science environment such as a controlled laboratory setting. This application crosses over into the realm of professional service robots. Indeed, robotic manipulators are being used in chemical and biological laboratories to handle and transport samples with high speed and precision, and automation in life science applications is increasing dramatically [13–15]. Later chapters of this book will address specific examples and case studies. The reader is encouraged to explore Chapman's review of lab automation, which focuses on specific examples such as automated mapping of the detailed structure of a protein, cell culture systems, sample storage and retrieval, and information management systems [13].

4.2.2 Design of Automation Systems

Automation is defined by Parasuraman and Riley as, "a device or system that accomplishes (partially or fully) a function that was previously, or conceivably could be, carried out (partially or fully) by a human operator" [11]. When considering automation for life sciences, one must first consider the degree to which the task will be automated, the subtasks of the procedure to be automated, communication between the human operator and machine, and more traditional HCI issues (usability, human factors, reliability, and safety). What to automate is typically determined by identifying functions that humans do not wish to perform, or cannot perform as accurately or reliably as machines.

Clear in the literature is a need to maintain a human in the loop, even when incorporating automation into a given application [16]. Humans are able to make well-formed decisions even with an absence of complete or correct information. Additionally, humans possess retention skills that aid in problem solving [17]. These abilities establish confidence in the reliability of an automation system, since the human operator can resume manual control when the environment changes, or when subsystems fail or encounter unexpected states.

In discussing automation, and in particular human interaction with automated systems, it is helpful to categorize the degree and nature of the automation. A number of autonomy scales have been proposed in the literature. A common taxonomy is based on ten levels of autonomy (LOA) and is summarized in Figure 4.1.

This scale was combined with a four-stage model of human information processing [19–21] and proposed as a revised taxonomy for automation [18]. These four stages include acquisition and sensory processing; analysis and perception/working memory; decision making; and response and action selection. The model for types and levels of automation is depicted in Figure 4.2.

For the acquisition stage of information processing, automation can be in the form of sensors that scan or observe the environment and provide data to the operator. In the most basic of terms, this can mean incorporating sensors into a system and relaying that data to a human operator or to the next automation stage. Acquisition can also involve the organization of incoming information according to some

HIGH 10. The computer decides everything, acts autonomously, ignoring the human.
9. Informs the human only if it, the computer, decides to.
8. Informs the human only if asks, or
7. Executes automatically, then necessarily informs the human, and
6. Allows the human a restricted time to veto before automatic execution, or
5. Executes that suggestion if the human approves, or
4. Suggest one alternative.
3. Narrows the selection down to a few, or
2. The computer offers a complete set of decision/action alternatives, or
LOW 1. The computer offers no assistance: Human must take all decisions and actions.

Figure 4.1 Levels of automation of decision and action selection. (*After:* [18].)

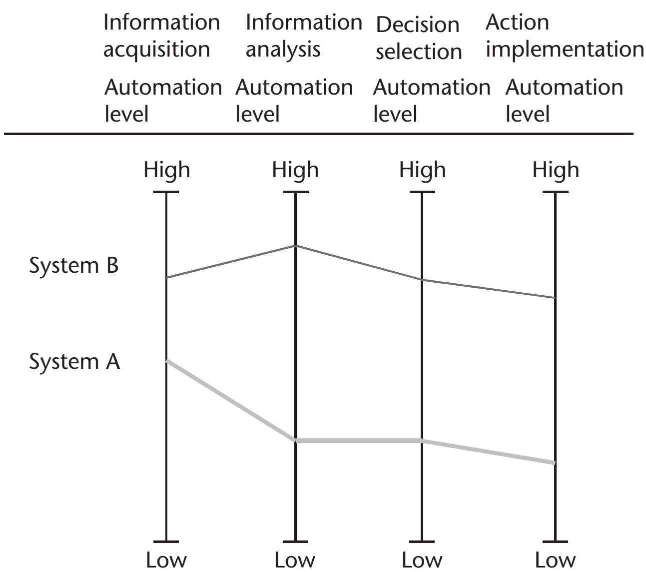

Figure 4.2 Levels of automation incorporated with four stages of human information processing. (*After:* [18].)

predetermined criteria, and then indicating subsets of the data or information for the operator.

The analysis stage involves cognitive functions such as working memory and processes of inference drawing. This stage can be automated in a basic sense by applied extrapolation or prediction to incoming data, or in a more advanced way by integrating information that has been collected into a single value or piece of information for the operator.

Decision making is automated via methods that select among several alternatives. One approach is the incorporation of conditional logic operations that select from a number of predefined alternatives. As emphasized by Parasuraman and coauthors [18], these automated decision making systems make explicit or implicit assumptions about the value or cost of a given outcome, which can be uncertain.

Finally, automation of action is in the form of machine execution, replacing actions performed by the human operator. Such actions can be manual physical tasks, such as the sort and staple options on many photocopier machines.

Alternative definitions and taxonomies of levels of automation are presented in [22–25], including the introduction of adaptive automation (also termed adjustable autonomy), where the user or the machine can initiate changes in the level of automation. An application of adjustable autonomy for micro assembly is discussed in [26], where human in the loop operation is desirable due to the complexities of the microscale environment, but some degree of automation of the machine improves overall system performance.

Based on the LOA scale presented here, Parasuraman et al. propose a framework for automation design that can be applied to systems for life science automation, shown in Figure 4.3. As represented in the figure, automation can be applied to any of the four stages of human information processing (acquisition, analysis, decision, action), and more than one stage can be automated in any given system. After deciding which stage(s) will be automated, the level of automation that should be applied must be determined. Inherent in this decision are many trade-offs, and the process will likely be iterative. Any specified level of automation for a given stage should be thoroughly evaluated to determine the primary and secondary consequences of the automation. Primary criteria are focued on direct impact on human performance, while secondary criteria include reliability, costs, ease of system integration, efficiency/safety trade-offs, and many more.

Note that any manifestation of automation can be adaptive, where the level and/or type of automation could vary depending on situational demands during operational use. Such adaptability can be automated itself, or controlled by the human operator.

Human-centered automation systems should be designed such that the human is not left with a fragmented or difficult job. Specifically, task allocation between the human and the automation should be such that the performance of the team exceeds that of the individuals. Key points to consider are assurance that the human can monitor the system, that the operator receives sufficient feedback on the state of the system, and that the behavior of the automation system is predictable in that the human is able to form a reliable mental model of the machine's operation [6, 19].

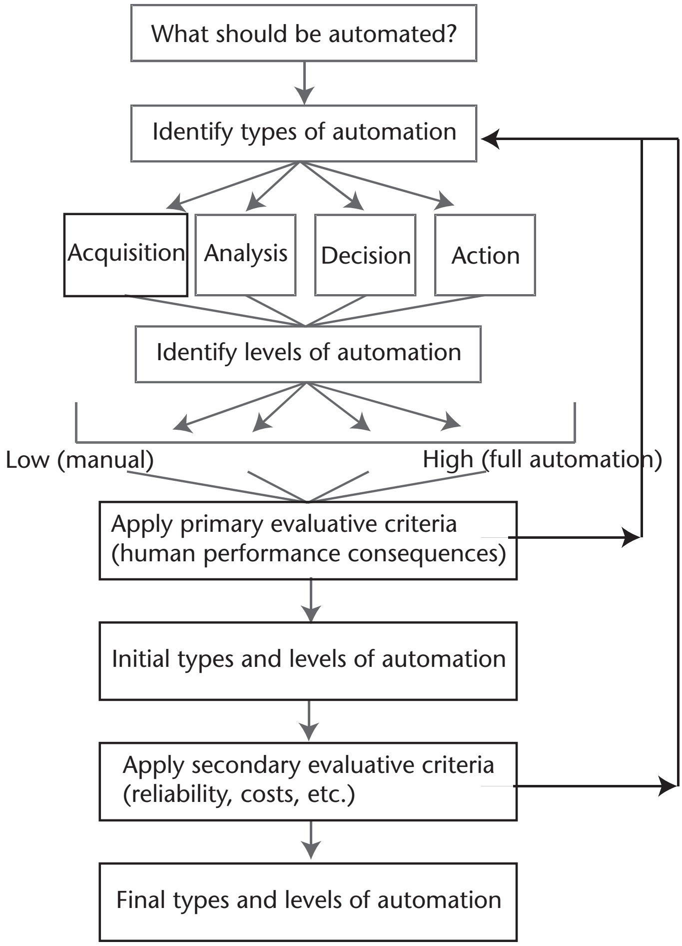

Figure 4.3 Framework for automation design. (*After:* [18].)

4.2.3 Performance of Human-Machine Systems

When automating tasks or systems that were formerly controlled manually, human activity is not simply replaced by machine, but instead human activity is changed in potentially unintended and unanticipated ways [11]. As a result, the automation system presents new and unique coordination demands on the human operator [27]. Given these new demands on the human operator, studies of human performance with human-machine and human-automation interaction systems are increasing. Indeed, these performance criteria can be used to determine the degree and type of automation that is suitable for the system.

Typically performance is measured in the resulting human-machine interface system, comparing task performance to the equivalent manual system. It is expected and desirable that both human and system performance are enhanced by automation, but the degree of performance enhancement is highly dependent on the types and levels of automation that are incorporated in the man-machine interface system. Human interaction with automation has been studied from a number of perspectives, including theoretical analyses, laboratory experiments, modeling, simulation, field studies, and analysis of real-world systems and accidents.

Four primary performance measures are presented here, as they are used in the automation design framework presented by Parasuraman et al.: mental workload, situation awareness, complacency, and skill degradation [18]. Mental workload reduction is a clear benefit of automation systems, since reducing operator workload (be it cognitive or even physical) can free up the operator to accomplish other tasks simultaneously. However, if the automation system is difficult to initiate, or if the operator is required to manually provide significant amounts of data to the system for automated analysis and decision making, the intended outcome of mental workload reduction can actually result in increasing load. Situation awareness is another performance measure. If the automation system is handling decision making or is updating an environment model, the human operator may be unaware of such updates compared to if they make such changes themselves. This lack of awareness can affect the ability of the human operator to form a sufficient mental model of the automation system's processes, increasing the probability of errors should the human operator need to regain manual control or override of the system. Third, if the automation is not reliable, the operator may become complacent and may not be aware of errors in the automated processes, basing future actions on incorrect outcomes. Finally, when decision making processes are automated, cognitive skills of the human operator can be degraded as they are no longer processing data, analyzing potential actions, and making such decisions themselves.

In addition to these primary performance criteria, based on the performance of the human and machine system, there are a number of secondary criteria which can be used to determine the utility of automation for a particular subtask or system. These secondary measures include, among others, the reliability of automation and the cost of decision/action outcomes. Reliability is often measured in probabilistic terms (mean time to failure, or raw values normalized to one), and there are consequences of poor reliability in terms of operator trust of the system, leading to underutilization of the automation. In such cases, other benefits, in terms of the primary performance measures, are lost. In terms of cost, factors such as the risk involved in the system, and the potential benefit or harm that could come to the human operator or those in the vicinity of the automated system, must clearly be considered. Such considerations can influence not only the selection of subtasks to automate, but the level of automation that is implemented.

A number of other performance measures are available for review in the literature, including neglect tolerance (a measure of how a system's current task effectiveness degrades over time when the system is neglected by the user), task effectiveness (how well the operator-automation system accomplishes the task), robot attention demand (the fraction of total task time that the human operator must attend to a given automated system), fan-out (the number of automated tasks that the human operator can simultaneously control), and interaction effort (the amount of time required to interact with the automated system) [28]. A study of the effects of automation on reliability is presented in [29]. Additional studies of human performance with automation systems are presented in [6, 12, 30], with a focus on situation awareness and workload. Leveson and Palmer studied error reduction via automation design [31].

These numerous performance criteria serve as a guiding principle in the iterative human-machine and human-automation system design process, and selection of performance criteria will vary according to the application and desired outcomes.

4.2.4 Human-Machine Teaming

When considering teaming between humans and machines, there are two primary topics for discussion: the architecture of the team, and task allocation. Team architectures are focused on how to organize teams of humans and machines, including the optimal number of human and machine team members. Research on teaming architectures seeks to identify situations which require various structures, for example authoritarian, hierarchical, or democratic [32].

In work by Scholtz, the role of the human is proposed as a defining aspect of human-machine teaming, with potential roles including supervisor, operator, teammate, mechanic/programmer, and bystander [33]. The supervisor is responsible for monitoring and controlling the overall situation and has sole responsibility for changing the larger goals and/or intentions of the robot or machine system, while the operator is able to modify internal software or models when the robot or system behavior is not acceptable. The mechanic deals primarily with the physical interventions with the system, but must be able to determine if the interaction has the desired effect on system behavior. The peer serves as a teammate to the robot or machine, and can give commands within the larger goal/intention framework defined by the supervisor. Finally, the bystander has a subset of actions available for interacting with the system. Scholtz's categorization of potential roles for the human are based on work by Kidd, who notes that human skill is always required in robotic systems, and that the goal of the designer should be to support and enhance human skill rather than substitute the robot for the human [34]. Specifically, he argues for developing robotics and human-machine systems such that humans can be more productive and efficient, for example by using machines for routine or dangerous tasks. Indeed, studies in both human-computer and human-machine interaction have demonstrated that performance of complex tasks improves when the system is designed to support rather than eliminate the human [35, 36]. In her work, Scholtz focuses on situational awareness as a measure of system effectiveness [33], recalling the three levels of situational awareness defined by Ensdley [37]. This taxonomy defines level 1 as perception of cues, level 2 as the ability to comprehend or integrate information and determine relevance to specific user goals, and level 3 as the ability to forecast future events and dynamics based on the perception and comprehension of the current system state.

In contrast to studies of team architectures, research on task allocation seeks to balance the skills of human and machine for a given task. In applications such as teleoperation, it is straightforward to utilize the controllability of the robotic manipulator to damp out tremor from the human operator, while in other applications the proper allocation of tasks may not be so straightforward. Research also seeks to determine how to build systems with dynamic task allocation, perhaps based on human workload. One study has investigated the efficiency of human-robot interactions for shared-control teleoperation with adjustable robot autonomy in order to reduce human workload, with promising results [38]. Through experiments, they showed that a shared control scheme is more tolerant to neglect, and results correlated well with measures of workload and ease of use. In another study, Marble et al. examined how the human operator was able to work with the machine at varying levels of autonomy (related to task allocation), with a focus on situation awareness and task performance, for a search and rescue task [39]. They found that participants were able to maintain awareness of the completeness of the task in all modes of autonomy, regardless of user experience with robotic systems. Additionally, they found that operators differed in their ability to function with higher levels of autonomy, with some users fighting the robot for control. Finally, they found that performance in the shared mode benefited from practice, indicating that as robot autonomy increases in a system, there may be an increased need for training of the human operator so that they may understand how and why the robot or machine will exhibit various behaviors.

When developing a human-machine interface for life science automation, therefore, the roles of human and machine must be clearly defined in the context of the task. Once roles are defined, then the degree of autonomy of each component can be specified, and tasks can be allocated to human and machine in a manner that exploits the strengths of each participant. It should be noted that safety is of great import in human-machine collaborative environments, especially as the human works in close proximity to the machine. The literature addresses safety in human-robot collaborative settings, which can be extrapolated to human-machine interactions for the life sciences. For example, Heinszmann and Zelinsky have proposed a control algorithm for robot manipulators, such as those that may be used for automation of pick and place tasks, which results in predictable and understandable robot actions, and limited forces between the robotic device and its environment [40]. In related work, Kulic and Croft have derived a measure of danger during human-robot interactions that can be explicitly computed based on impact force during potential collisions between the human and robot. Motion strategies that minimize the danger index have been developed and demonstrated both in simulation and experimentally [41, 42]. They extend their work to incorporate measurement of physiological signals to determine human response to robot motions, with decreased anxiety when safe planning is carried out for high speed operation of the robot [43].

4.2.5 Communication

Communication in human-machine systems can be categorized as direct or mediated [32]. Direct human-machine communication is accomplished via speech, vision, gesture, or remote operation of manipulators (teleoperation). Mediated human-robot communication is accomplished via virtual environments, graphical user interfaces, and collaborative software agents.

Teleoperation, or remote control via robotic manipulators, remains a primary mode of interaction in human-machine systems. Such systems can be multimodal, reflecting visual, auditory, and/or haptic feedback from the remote site to the human operator. These systems have been quite successful in a number of applications such as space robotics and surgical robotics, but they can also be expensive and limited in scope. Challenges arise such as limited degree-of-freedom of control, limited feedback to the operator, increased cognitive demand on the operator, and the potential for communication delays between master and slave. Other direct means for communicating with machines and systems include speech, gestures, facial expressions, body posture, and written gestures [44, 45]. Often, however, inclusion of such communication modalities between humans and machines are limited due to scientific challenges in speech recognition, natural language processing, and computer vision algorithms.

As a result of the challenges of direct communication in human-machine interfaces, we are often relegated to use physical interaction and interfaces, which can include computer terminal interfaces, touch screens, physical haptic interfaces, and other input devices. For automation applications, often the physical interface is used not only to operate but also to program the machine to carry out the desired tasks. One common approach is programming by demonstration [46]. The goal of programming by demonstration is to simplify complex machine programming by allowing the human operator to carry out the specified task as desired, and then recreate the actions with the machine. This can be done either within the real environment or in a simulated environment, and sometimes with the use of synthetic aids [47].

4.3 Current Research

Given the background on human-machine interactions discussed in the previous section, some current research trends in the field will now be presented. Specifically, this section will focus on physical haptic interaction between human and machine. In the context of the topics presented thus far, recent research advances in haptic human-machine interaction will be presented. Focus areas include performance specifications for haptic devices, human-machine teaming architectures, and human performance enhancement via haptics.

4.3.1 HMI Interaction Via Haptic Devices

One consideration in human-machine interfaces is the design requirements for the physical device. The proper design of any machine requires a well-defined set of performance specifications. The requirements for device design become even more important when the human operator is physically coupled to the interface, and when haptic (force) feedback is provided to the operator. Although much work has been accomplished in the field in general (see, for example, the surveys [48, 49]), hardware specifications for haptic interfaces that relate machine parameters to human perceptual performance are notably absent. The absence of such specifications is most likely because haptic interface performance specifications must consider issues of human perception, which is complex in nature and difficult to assess quantitatively. With the recent introduction of several commercially oriented haptic devices and applications, the need for a set of specifications to guide the cost-optimal design of haptic devices is that much more pronounced.

The vast majority of the research literature related to this topic has generally either focused on quantitative measures of human factors, measures of machine performance independent of human perception, or the effects of software on the haptic perception of virtual environments. Regarding the first area, psychophysical experiments conducted by several research groups have quantified several haptic perception characteristics, such as pressure perception, position resolution, stiffness, force output range, and force output resolution (for example, [50–54]). Since these experiments did not involve haptic interface equipment, however, they were not able to create a direct link between machine performance and human perception during haptic task performance.

Within the second area of research, optimal machine performance has been characterized in the literature, yet these measures are typically disparate from human perceptual measures. When designing high-performance equipment, designers seek to build a device with characteristics such as high force bandwidth, high force dynamic range, and low apparent mass [55, 56]. These are typically qualitative specifications, however, since the designers have little reference information regarding the quantitative effects of these machine parameters on the performance of humans with regard to perception in a haptically simulated environment. Several researchers have incorporated human sensory and motor capability as a prescription for design specifications of a haptic interface [57–59]. Such measures are logical, though indirectly related to haptic perception and most likely quite conservative for common haptic tasks. Colgate and Brown offer qualitative suggestions for haptic machine design that are conducive to the stable simulation of high impedances [60]. Though simulation of a high impedance is a useful and logical performance objective for a haptic device, the objective is not directly based upon measurements of human perception.

Finally, researchers have studied the effects of software on the haptic perception of virtual environments (for example, [61–63]), yet these experiments did not address the relationships between haptic interface hardware design and haptic perception. Recent work has addressed the relationship between haptic interface hardware and human perception, and in particular measures the effects of varying virtual environment force and virtual surface stiffness in a simulated environment on human perceptual capabilities in a haptic environment [64–66]. Virtual surface stiffness is of interest as a machine parameter because hardware selections, including position sensors and computers, can limit achievable virtual surface stiffnesses. A good discussion of the relationship between hardware and achievable surface stiffness is given in [60].

In one study [64], identification, detection, and discrimination tests were performed to characterize the effect of maximum endpoint force on the haptic perception of detail. Results indicate that haptic interface hardware may be capable of conveying significant perceptual information to the user at fairly low levels of force feedback (3N to 4N). While higher levels of force output in a haptic simulation may improve the simulation in terms of perceived realism, the results of these experiments indicate that high levels of force feedback are not required to reach maximum information transfer for most aspects of the haptic display of detail.

In a similar study [65], identification, detection, and discrimination tests were performed to characterize the effect of virtual surface stiffness on haptic perception of detail in a simulated environment. Results indicate that haptic interface hardware may be capable of conveying significant perceptual information to the user at low to moderate levels of simulated surface stiffness (approximately 400 N/m when virtual damping is also present) for gross stylus-type perceptual tasks.

In a follow-up study [67], experiments were conducted to compare human perceptual performance in a real environment to performance in a simulated environment for two perception tasks: size identification and size discrimination. Findings indicate that performance of size identification tasks with haptic interface hardware with reasonable maximum force output can approach performance in real environments, but falls short when virtual surface stiffness is limited. For size discrimination tasks, performance in simulated environments was consistently lower than performance in a comparable real environment. Interestingly, significant variations in the fidelity of the haptic simulation do not appear to significantly alter the ability of a subject to identify or discriminate between the types of simulated objects described herein.

These findings can be extrapolated to teleoperation environments which may be more common in life science applications, where forces at the slave manipulator are reflected to the human operator, and they give some insight into the requirements on the master manipulator's force reflection capabilities. To insure good performance of size identification tasks, designers of haptic interfaces should first aim to create simulated environments with high virtual surface stiffness, and should treat maximum force output of the haptic device as a secondary design goal, since limited force output had an insignificant effect on performance when compared to performance in a real environment. For size discrimination tasks, designers of haptic devices should aim to reach recommended minimum levels of maximum force output *and* virtual surface stiffness (3N and approximately 470 N/m, respectively) to insure acceptable performance, but should note that this performance will never reach the level that can be attained in a comparable real environment.

4.3.2 Teamwork

While teaming of humans and machines can strictly refer to humans working in close proximity to mobile robots or industrial automation, teaming of human and teleoperated robotic agents is also a feasible architecture for task completion, and one that has clear application for life science applications where the existence of a human in the loop is of great importance, yet the capabilities of the machine or robotic device should be exploited. In one study, a simplified, hypothetical extravehicular activity (EVA) assembly task featuring human-robot teaming was simulated with hardware-in-the-loop to study the human-robot interaction problem [68]. The task was purposefully designed to require more than two hands and, therefore, multiple agents so that meaningful interactions could take place. A long structural beam, too awkward for one agent to handle alone, was inserted into a fixed socket and pinned in place. In the experiment, the number of information channels and types of communication were varied to study the effects of such means on performance of the assembly task. Three communication modes were compared with and without force feedback provided via a haptic device. The three modes included force feedback to the teleoperator via a visual display, visual feedback of force combined with verbal cueing from the worksite human to the teleoperator, and visual feedback of force combined with verbal and gestural cueing from the worksite human to the teleoperator.

The assembly team consisted of one robot and three humans. One human, the coworker, is collocated with the robot at the worksite, while the other two, the teleoperator and the monitor, are placed in different remote locations. Performance metrics for the assembly task included task success, task completion time, maximum contact force/torque, and cumulative linear/angular impulse. Task success describes the degree to which a team was able to meet all task objectives. Task completion time reflects how efficiently resources were used in accomplishing the task. Maximum contact force/torque quantifies the risk of hardware failure or damage due to excessive momentary peak loads at the beam-socket interface. Cumulative linear/angular impulse quantifies the risk of hardware failure or damage due to excessive wear and tear as a result of extended contact at the beam-socket interface [69].

The most significant result of this experiment is the comparison of maximum contact force in the beam receptacle across pairs and feedback modes. In the case of no force feedback, where the teleoperator was limited to only a visual display of the forces and torques in Robonaut's arm, peak forces ranged between 40N and 110N. As additional feedback modes were added, such as verbal cues and gesturing, peak forces tended to decrease. In fact, in the case where visual force information, verbal cues, and gestures were all employed, peak forces were roughly half that of the other nonforce feedback trials. When the teleoperator was provided with force feedback via a haptic device, peak forces were quite consistent and ranged between 30N and 50N. Standard errors were much smaller for the force feedback case. This is a significant result due to the fact that large forces in the receptacle are transferred to the robot during constrained motion and contact, leading to larger loads on the hardware. When the teleoperator had kinesthetic information regarding the contact forces, a significant reduction in peak forces was observed, regardless of the other methods of communication between teammates. Differences in the roles played by each subject (task leader or teleoperator) were insignificant for this comparison.

For applications in micro- or nanomanipulation, or in a laboratory setting, it will be beneficial to provide multiple modalities of feedback to the human operator, especially haptic feedback of the forces at the slave environment via the operator interface, in order to minimize damage to the biological sample.

4.3.3 Robots for Performance

Virtual environment (VE) technology offers a promising means of enhancing human performance and training humans for motor skill acquisition. Computationally mediated training has many potential advantages over physical training like lower risk and cost, and better data collection and evaluation. Training in VE aims to transfer what is learned in the simulated environment to the equivalent real-world task. Virtual training can be designed either to provide a *virtual practice medium* that matches the targeted physical medium as closely as possible, or to behave as a *virtual assistance* to improve training effectiveness by providing additional feedback in ways that are possibly not realizable in the physical world.

Most forms of interaction with computerized simulations involve only visual and auditory information. However, it is shown that the addition of haptic feedback to virtual environment simulations provides benefits over visual/auditory-only displays via reduced learning times, improved task performance quality, increased dexterity, and increased feelings of realism and presence [69–74].

To exploit performance enhancement and training capabilities of virtual environments with haptic feedback, various virtual assistance paradigms have been proposed. These training paradigms are inspired by various motor learning theories and are realized through different assistance schemes such as promoting more practice, demonstrating a strategy, augmenting feedback error, and reducing feedback error.

Among these methods, the most common form of haptic assist is achieved through the introduction of forbidden zones in the workspace via so called *virtual fixtures* [75]. Virtual fixtures are analogous to the use of training wheels when riding a bicycle, or a ruler when drawing straight lines. These virtual fixtures have been shown to significantly improve task performance in virtual environments [76, 77]. However, since the feedback provided by virtual fixtures is independent from the dynamics of the system to be learned, and because this feedback becomes available intermittently only to prevent large errors, from the perspective of training, virtual fixtures provide nothing more than a safer medium for practice. The assistance provided by virtual fixtures is not aimed to assist the mechanism of learning, but is designed merely to facilitate safer practice. Learning still takes place through *virtual practice*.

Another form of virtual trainer is motivated through teaching by demonstration. In these *record and play* strategies [78–82], the dynamics of an expert are recorded while performing the task and these dynamics are played backed to the novice to assist learning. In this kind of assist, the novice is not actively involved in the task during training. Once the preferred strategy to achieve the task has been played back a couple of times, the novice is allowed to practice to mimic the demonstrated dynamics. This paradigm does not account for the differences due to user-specific dynamics, and also prevents the novice from forming their own strategies.

Patton et al. [83] propose to train reaching movements by generating custom force fields designed to drive subjects to adopt to a prechosen trajectory. This strategy is based on aftereffects of adaptation and aims to alter the feedforward command in the central nervous system. However, this approach is not effective for long-term training since the aftereffects tends to wash out after relatively short periods.

In [84], Todorov et al. utilize error augmentation strategies to speed up human motor learning of a dynamic task. By amplifying the instantaneous error, modified dynamics are displayed to the user to promote faster convergence of error-based adaptation mechanisms. Capitalizing on a form of assistance not realizable in the physical world, this technique resulted in significant increases in learning rates. The limitation of this technique lies in its applicability to complex tasks since augmenting the error in these cases can significantly degrade performance, rendering successful task completion infeasible.

Finally, error reduction has been implemented through a *shared controller* for performance enhancement and training [85–87]. O'Malley and colleagues have proposed shared control as an active assistance paradigm where the feedback is provided by a controller, which is dependent upon the system states, as depicted in Figure 4.4. By dictating the type and level of active control between the computer and the human on the virtual system's dynamics, shared control constitutes the most general form of virtual assistance or training. Virtual fixtures, record and play strategies, and transient dynamics amplification are all encompassed as special cases of shared control since these paradigms can easily be realized through shared controllers of specific structures. Shared control has been shown to improve task performance in both physical and virtual environments [88, 89]. Other shared controllers have been proposed for training in minimally invasive surgery [90]. However, effects of these controllers on training is yet to be studied. Finally, the authors' implementation of error reduction with a shared control architecture is shown to improve performance of the task as well as affecting motor skill acquisition through improved retention from one training session to the next compared to practice without assistance [85].

These shared control techniques can be used to create intelligent teleoperation systems for life science applications that go beyond reducing operator tremor. Forbidden regions of the workspace can be established, along with guidance forces to carry out various tests such as analysis of material properties at the micro- and nanoscale. When extrapolated to the training scenario, standard laboratory practices could be incorporated into training protocols for young researchers who must manipulate small-scale structures in difficult environments. Such cues can all be conveyed via the haptic operator interface.

4.4 Future Issues

A number of key research directions have been proposed as the result of a DARPA/NSF study on human-robot interaction, which directly apply to human-machine

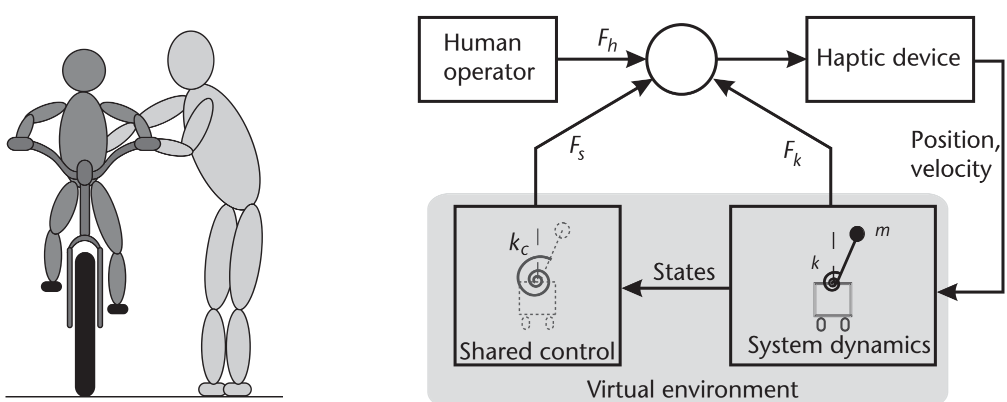

Figure 4.4 Schematic representation of shared controller, where an expert collaborates with the operator. Block diagram representation shows implementation of shared controller with a virtual environment displayed via a haptic interface. The shared controller acts on the states of the system to be controlled.

interface issues in life science automation [32]. These include studies of human intervention with different levels of autonomy; interaction modalities that can be used in various physical environments; and the development of roles for robots and humans within teams. In this spirit, the following section highlights several unique challenges to the field of human-machine interfaces and interactions applied to life science automation and micro- and nanoapplications.

4.4.1 Challenges for Applications in Life Science Automation

A significant challenge for human-machine interaction in the life sciences is the degree of dependency on individual applications that exists. While some procedures such as pick and place tasks may be quite standard and could be completed with a common machine hardware platform, often the laboratory environment presents design constraints for the system, resulting in a need for customized hardware for each application of interest. Tasks may require a wide range of degree of freedom from a manipulator to be completed, or may require a range of end-effector tool options. Additionally, tasks may lend themselves to different interaction modalities, be they haptic, audio, or visual. The geometry of the workspace, and the task to be completed, will define sensor resolution requirements (for controlled positioning tasks) and actuator requirements (for meeting speed and load carrying specifications). Due to the variations in environment and task specification, all-inclusive solutions are unlikely. Therefore, designers of human-machine interfaces for life sciences must consider the issues of what tasks should be automated, how tasks should be allocated between human and machine, performance requirements for the collaborative system, and teaming architectures presented earlier in the chapter to ensure a successful solution.

4.4.2 Challenges for Micro- and Nanoscale Applications

Over the last decade, considerable interest has been generated in building and manipulating nanoscale structures and objects. Experiments have been conducted to interact with nanoparticles, molecules, DNA, and viruses [91–94], measurement of mechanical properties of carbon nanotubes [95], and bottom-up nanoassembly [96, 97]. Nanomanipulation refers to the use of external forces for controlled positioning or assembly of nanoscale objects in two or three dimensions through cutting, drilling, twisting, bending, pick and place, push and pull kind of tasks [98]. Figure 4.5 depicts some basic mechanical manipulation tasks that can be performed at nanoscale using an AFM cantilever [99].

Due to limitations in current understanding of nano-scale phenomenon, nanomanipulation systems are typically implemented using a telerobotic setup [100–103]. Figure 4.6 shows the setup of a proposed nanomanipulation system. The human operator commands a slave robot through the master robotic interface. During manipulation, the operator may be provided force or visual feedback, from the environment, or both. Visual feedback is useful for locating the objects of interest, whereas haptic feedback plays an important role in contact and depth perception.

Several research efforts have focused on the development of scanning probe microscopes (SPMs) for nanomanipulation [93, 102–104]. These systems are

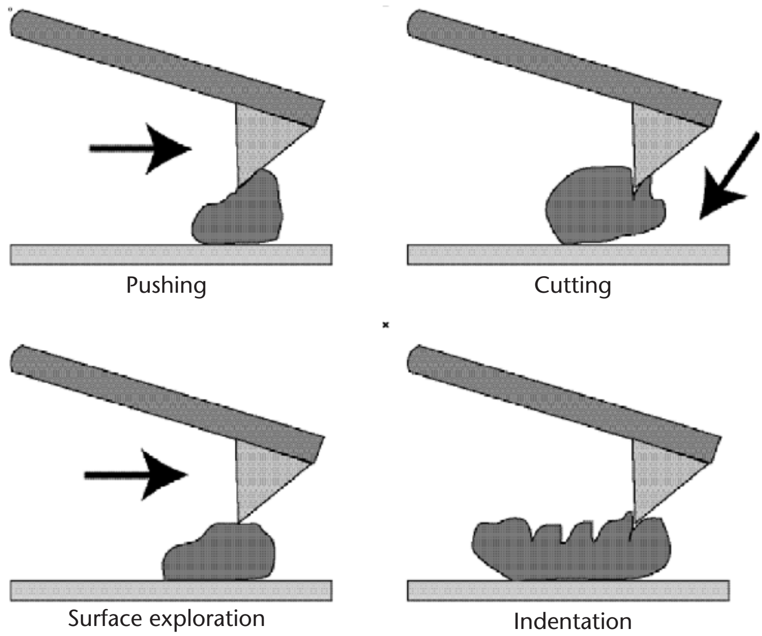

Figure 4.5 Possible nanomanipulation tasks using an AFM cantilever: pushing, cutting, surface exploration, and indentation. (*After:* [99].)

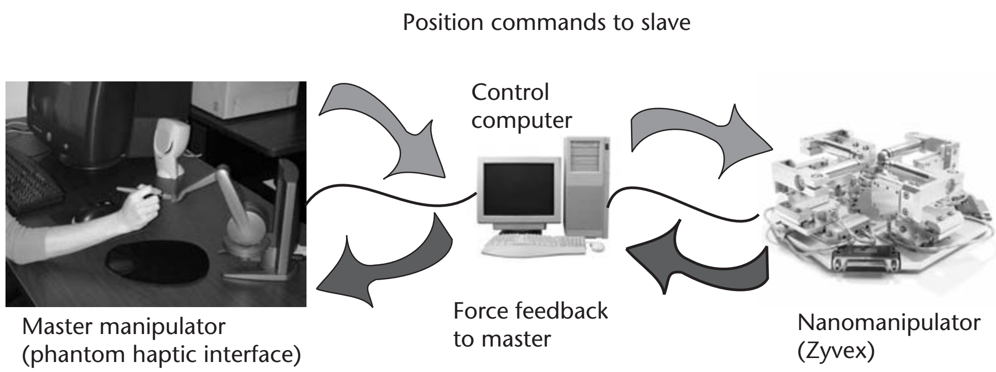

Figure 4.6 Typical nanomanipulation setup. A human operator commands the slave nanomanipulator. Force feedback to the operator may or may not be provided.

generally restricted to two dimensions with a very limited third dimension. Using a scanning tunneling microscope (STM) probe, manipulation of atoms or molecules can be achieved by applying voltage pulses between the probe and the surface of the sample. This was first achieved by Eigler and Schweitzer in 1990 [104]. Sitti and Hashimoto [102] present the design of an AFM-based telerobotic nanomanipulation system. They successfully positioned latex particles with 242- and 484-nm radii on Si substrates, with 30-nm accuracy, using an AFM cantilever as a manipulator. They adopt a two-stage manipulation strategy. First, the image of the particles is obtained using AFM tapping mode. Then the particle is pushed by moving the substrate with a constant velocity. A virtual reality interface including 3D projection display and force feedback for SPM-based manipulation, known as the nanoManipulator, is presented in [93, 103]. In SPM-based nanomanipulation systems, such as these, there is no real-time visual feedback from the environment. Following their experience with the nanoManipulator, Guthold et al. [93] reported: "Force feedback has proved essential to finding the right spot to start a modification, finding the path along which to modify, and providing a subtler touch than would be permitted by the standard scan-modify-scan experiment cycle." Hence, haptic feedback is critical in these nanomanipulation systems.

As compared to the SPM-based nanomanipulation systems, scanning electron microscopy (SEM) or transmission electron microscopy (TEM) based systems provide real-time visual feedback from the nanoscale environment. Dong et al. present a 16 degree of freedom (DOF) nanorobotic manipulator that operates inside a field emission scanning electron microscope (FESEM). Their system supports up to four end-effectors and has a workspace of 18 mm × 18 mm × 18 mm. The relatively large workspace, multiple end-effectors, and large number of DOFs allow complex operations with such a 3D nanorobotic manipulator. The authors report nanorobotic manipulation to be more effective in constructing complex nanostructures than self-assembly and SPM-based systems. These systems, however, are restricted to operate in vacuum.

A comparison of SPM-based systems with SEM/TEM-based systems is presented in Table 4.1. The primary limitation of SPM-based systems is their inability to image and manipulate simultaneously. Due to drift and hysteresis, the position of tip relative to the sample may change over time. Hence, during manipulation, the user relies only upon haptic feedback. SEM/TEM-based systems, on the other hand, provide real-time visual feedback but present challenges in force sensing. The nanorobotic manipulation systems provide a larger workspace for operation than SPM-based systems, but cannot match the position resolution of SPMs. AFMs can also operate in liquids, making them particularly suitable for biological applications.

Table 4.1 SPM Versus SEM/TEM-Based Nanomanipulation Systems

System Description	*SPM-Based Nanomanipulators* *Modified SPM (AFM/STM) System*	*Nanorobotic Manipulation Systems* *Robotic System Operates Within SEM/TEM*
Number of probes	1	Multiple independent probes
Image resolution	1 nm	~ 5 nm
Position accuracy	1 nm	5–10 nm
Visual feedback during manipulation	No	Yes
Haptic feedback during manipulation	Yes	Some systems
Force/position sensing	Yes	Some systems
Biological sample manipulation	AFM-based systems	No

Haptic feedback has been reported to be critical for nanomanipulation [93]. This is especially true for SPM-based systems, where no real-time visual feedback is available during manipulation. Nanorobotic manipulators that operate inside SEM/TEMs can also benefit from incorporation of haptic feedback as it helps improve sensation of contact. Nanoscale objects could be fragile, and force feedback helps the user apply controlled forces for manipulation.

Various methods of force feedback have been used for SPM-based systems. An AFM cantilever can be used as a nanoscale force sensor. Using an optical detection system, coupled normal and frictional forces can be sensed inside an AFM [100]. Piezoresistive force sensors can be incorporated into the AFM probe during fabrication to provide a compact manipulation system [101, 105]. The STM-based nanomanipulator presented by Taylor et al. [103] provides a method of feedback of surface topography during manipulation using virtual springs. In later work [93], the authors report that regions of high and low friction can also be represented as high or low regions topologically.

Force sensing in nanorobotic systems that operate inside SEM/TEMs is more challenging. Arai et al. present a carbon nanotube–based pico-Newton level force sensor [106]. The nanotubes are attached to an AFM cantilever and their deformation is measured from SEM images. We are not aware, however, of any use of this information for force feedback. The range of this carbon nanotube–based sensor is limited to pico-Newton levels. In addition, the nanotube may not be the ideal end-effector for general purpose nanomanipulation due to its high length-diameter ratio. Hence, there is a need for improved force sensors for such systems.

Gupta, Patoglu, and O'Malley present a vision-based force sensing scheme for a nanorobotic manipulation system that operates inside an SEM [107], shown in Figure 4.7. An AFM cantilever is used as the end-effector and is visually tracked to

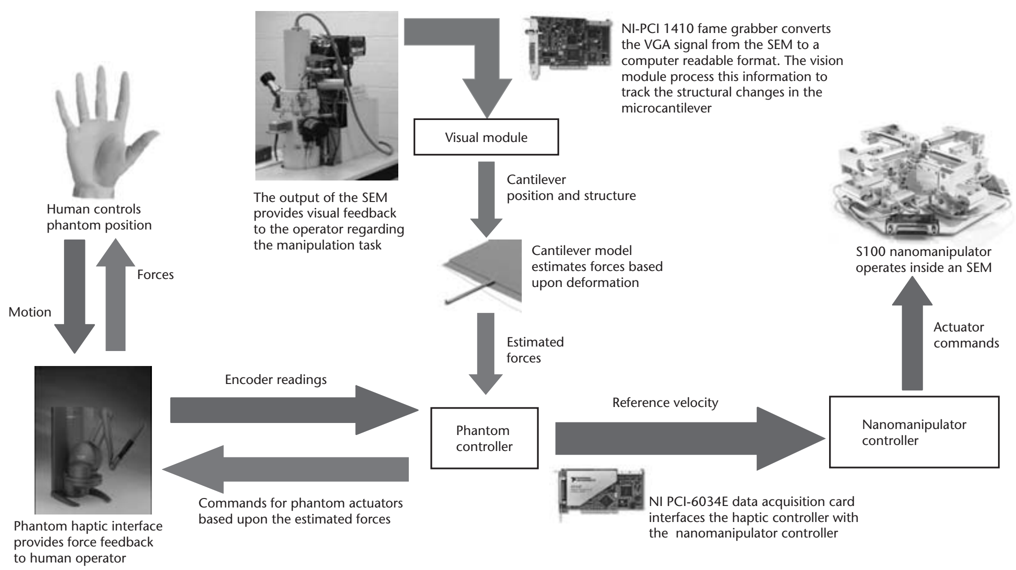

Figure 4.7 Overview of nanomanipulation system proposed by Gupta et al. [107].

measure its deformation. The work is motivated from similar work by Greminger and Nelson [108], who use visual template matching for tracking of a microcantilever to sense nano-Newton forces at the micro level. Their approach of template matching, however, is not suitable for our application of nano-manipulation due to variable occlusion of the cantilever and loss of coherence in consecutive frames, due to the nature of implementation of the magnification functionality in the environmental SEM (ESEM). Hence, a global search strategy is proposed that can be used for force sensing directly or to find a suitable point of initialization for subsequent template matching.

As described, many of the challenges in human-machine interaction at the nanoscale, and extended to the microscale, are based on the issues of sensing and actuation of micro- and nanoscale manipulators. Additionally, the decisions of what modalities and data to render to the human operator must be made with the understanding that forces of interaction at these scales differ from macroscale physics, which humans are more familiar dealing with.

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