Remote Supervisory Control of a Humanoid Robot

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Abstract

For this demonstration, participants have the opportunity to control a humanoid robot located hundreds of miles away. The general task is to reach, grasp, and transport various objects in the vicinity of the robot. Although remote "pick-and-place" operations of this sort form the basis of numerous practical applications, they are frequently error-prone and fatiguing for human operators. Participants can experience the relative difficulty of remote manipulation both with and without the use of an assistive interface. This interface simplifies the task by injecting artificial intelligence in key places without seizing higher-level control from the operator. In particular, we demonstrate the benefits of two key components of the system: a video display of predicted operator intentions, and a haptic-based controller for automated grasping.

Introduction

"Thousands of teleoperators have been built and used successfully.... But these teleoperators are poor and incomplete extensions of man, with only a small fraction of man's dexterity and man's many degrees of freedom." This quote from Johnsen and Corliss (1971) describes the state-of-the-art thirty years ago for robot control in uncertain environments. Although dramatic advances in hardware and intelligent control have been made over the past several decades, the essence of this quote remains true today. Robotic manipulation of the world (or some distant world) is primitive in comparison to what people could do themselves.

But despite its limitations, teleoperation remains the best way to solve many robotics tasks that lack the relative certainty of factory automation. Examples include hazardous waste disposal, planetary and undersea exploration, robot-assisted surgery, and emerging applications such as elder care. What these examples have in common is the need to exploit the unique capabilities of both humans and robots; neither can go it alone.

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The fundamental problems with remote manipulation are at least twofold: (1) From the perspective of *automatic control*, variation in circumstances from one instance of a task to the next makes general-purpose, automated solutions difficult to devise, even for a restricted class of tasks. The challenge for roboticists and artificial intelligence researchers is to manage uncertainty. (2) From the perspective of *manual control*, current forms of teleoperation suffer from considerable mismatch between robots and human operators, in terms of morphology, sensory input, and actuation. This leads to movements that are fatiguing for the operator due to excessive muscular and cognitive load.

Bridging the gap between automatic and manual control, is *human supervisory control,* whereby a human operator intermittently takes control of a process that is otherwise controlled by a computer (Sheridan 1992). Supervisory control involves both autonomy and intelligence, although the latter is normally attributed solely to the human operator. Approaches that also emphasize machine intelligence include systems for *mixed-initiative control,* e.g., (Adams, Rani, & Sarkar 2004), and *adjustable autonomy,* e.g., (Kortenkamp, Schreckenghost, & Bonasso 2000; Scerri, Pynadath, & Tambe 2002). One goal of these approaches, and of supervisory control in general, is to devise effective ways to shift more responsibility from human to machine.

Demonstration Overview

Our recent work has focused on teleoperation (1) as a convenient way to program robot skills by demonstration, and (2) as an effective way to convey operator intentions for mixed-initiative control. The latter is the focus of this Intelligent Systems demonstration, and participants have the opportunity to control Dexter, the UMass Amherst humanoid robot shown in Figure 1.

Commands are sent to the robot using a glove-like input device and standard TCP/IP communications. Feedback for the operator takes the form of a real-time video display of the robot's workspace in Amherst. Limited bandwidth and communication delays exacerbate the previously mentioned problems with teleoperator interfaces, and we expect participants to have considerable difficulty manipulating objects with Dexter's hands. Our goal for the demonstration is to show that a relatively small amount of artificial intelligence

Figure 1: Dexter, consisting of two seven-degree-of-freedom manipulators, integrated three-fingered hands with high-resolution tactile sensors, and a four-degree-of-freedom stereo camera head. Not shown are several webcams and a glove-like input device that enable remote operation over the Internet.

can go a long way toward mitigating operator errors as well as fatigue.

The first source of intelligence is a *predictor display* that augments the video stream with important information for human decision-making. Predictor displays are typically used to overcome communication delays by overlaying, for instance, a wire-frame model of the robot's future movements, e.g., (Kim & Bejczy 1993). However, predictor displays are also useful for conveying information about the human operator (Rosenstein, Fagg, & Grupen 2004).

More specifically, we use a set of closed-loop controllers to abstract and explain observed operator behavior in terms of actions that the robot can generate itself (Fagg *et al.* 2004). In this context, controllers are passive entities—monitors—that quantify the match between observed operator actions and putative operator intentions. In our implementation, we convey the degree of match between actions and intentions by the size of circles superimposed in the operator's video display. After visual confirmation of the best match, the operator turns control over to an automated system that runs the corresponding controller as an active entity, thereby generating movement to satisfy the intention.

Our controllers for automated movement implement a second source of artificial intelligence, first by using a computer vision system to guide coarse-grained movement of Dexter's hand toward the object that the operator intends to manipulate. Once the fingertips make contact with the object, a closed-loop controller then performs fine-grained motion of the arm and fingers to establish a robust grasp based on the "feel" of the object rather than pre-specified geometric models (Platt Jr., Fagg, & Grupen 2002). The operator can resume control at any time or else rest until the automated grasp completes, at which time he or she performs the next phase of the task. Even a small amount of autonomy, injected at the right time, can have a dramatic effect on the overall quality of the human-robot interaction.

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