Abstract—Many machines—from hydraulic excavators to mobile wheelchairs—are manually controlled by a human operator. In practice, the operator assumes responsibility for completing a given task at maximum utility, even though the optimal inputs may be unknown to the operator. Here we discuss a simple technique termed Blended Shared Control, whereby the human operator commands are continually merged with the commands of a robotic agent. This approach is shown to result in a lower task completion time than manual control alone when applied to a problem motivated by Zermelo’s navigation problem. Experimental results are presented to compare blended shared control to other types of controllers including manual control, heads up display, and haptic feedback. Trials indicate that the shared control does in fact decrease task completion time when compared to fully manual operation.

Index Terms—shared control, haptics, minimum time control.

I. INTRODUCTION

Despite the increased capabilities of autonomous control and with the exception of a few research prototypes, many machines—from hydraulic excavators to mobile wheelchairs—are still manually controlled by a human operator. The operator assumes responsibility for giving the inputs to cause the machine to complete a given task at maximum utility, for example in minimum time or with least energy consumption. However, even the optimal control solutions of simple nonlinear systems, such as the simple planar case of Zermelo’s problem, may be non-intuitive or otherwise beyond the capabilities of a human operator responsible for providing the control input. Consequently, manually controlled machines often are operated suboptimally. In an effort to draw the operator nearer some degree of optimality, an electronic agent may be given authority to share control with the operator.

Shared control (SC), teleoperation, supervisory control, manual control, and human-machine interaction are well studied areas and excellent books thoroughly address these topics [1], [2]. A distinguishing feature of each of these domains is that humans maintain some degree of authority within the control loop, as opposed to fully autonomous architectures for which the operator cedes practically all control to the robot.

In this paper, we loosely define shared control as a control scheme that causes the output or response of a system to be influenced (e.g., either indirectly or through direct action) by two or more agents, here considered to be a human agent (HA) or operator and an autonomous electronic agent (EA) or robot. The need for an operator to share control with a semi-autonomous machine often arises from a combination of physical limitations (i.e., the operator knows how to perform the desired motion but is physically incapable) and cognitive limitations (i.e., the operator has a lack of understanding, has finite processing capabilities, or is occupied with tasks of higher importance). The numerous embodiments of SC presented in literature can be categorized into one of several flavors as described in Fig. 1 and in the text below with illustrative examples of relevant academic research. The control inputs \( u = [u_1, u_2, u_3, u_4] \) to the machine may, for example, represent velocity commands to each DOF.

Traded control: The HA and EA may initiate, either on demand or automatically, a transfer of control to allow either fully manual or fully automatic control. Applications include aircraft autopilot systems for which the operator cedes low-level control authority during cruising but maintains full authority during takeoff and landing. Other examples of traded control include systems that allow recording and playing back of robot trajectories.

Indirect shared control through cues: The EA derives sensory cues based on programmed criteria. The cues displayed to the HA nominally influence the input \( u \) in a manner amenable to the stimulus. The EA does not directly influence the input to the machine. Examples include visual indications of suggested process inputs in the control of power plant systems [2]; and haptic feedback, e.g., for vehicle lane tracking [3], or for improved digging performance in hydraulic excavation systems [4]. This method necessarily requires hardware capable of providing this sensory cue, in addition to cognitive attention from the HA (who may already be starved for attention).

Coordinated control: The HA has full control of all DOF through a possibly lower-dimensioned input \( v \), yet the complexity of deriving these inputs is reduced by the EA. E.g., the EA may enable simpler control of end effector motion by handling the calculations of inverse kinematics; thus the HA is relieved of the burden of controlling each individual actuator [4], [5], [6], [7]. This is often implemented by establishing a virtual or practical constraint such as a manifold of lower dimension than the total DOFs upon which the operator’s inputs act. The constraint may be a mathematical formulation or a specific mapping from the input space of the operator interface device to the output space of the manipulator.

Collaborative control: A certain subset of inputs \( u \) are initiated from the HA with the remaining from the EA.
Examples include automobile cruise control (the HA controls steering while the EA modulates the throttle) and automatic parking [8] (the HA controls the throttle while the EA controls steering).

**Virtual constraint:** The EA modifies or disallows a subspace of HA commands—such as speed, proximity to obstacles, or type of payload—to satisfy an arbitrary constraint $g(x)$. For instance, an EA may prevent inputs that cause a wheelchair to collide with a wall while allowing all other inputs [9]. Some embodiments of fly- or drive-by-wire systems also may actively preclude dangerous or otherwise ill-advised operator inputs.

**Blended shared control:** The commands from HA ($u_i$) and EA ($u'_i$) are combined through some functional relationship $F$, so that changes in either input are immediately realized as input changes to the machine, for example in semi-autonomous wheelchair navigation [10], [11], [9], [12] and expert/apprentice scenarios for training in telesurgery applications [13].

The next section of this paper discusses a proposed structure for blended SC, and presents a particular example problem developed to demonstrate the new control approach. Then, we describe an experiment used to evaluate the blended SC approach in comparison to three alternative control methods. Finally, the results of the experiment are presented.

**II. BLENDED SHARED CONTROL**

Here, we discuss a proposed blended shared control (SC) architecture for a single input system, followed by experimental results for this and other types of SC.

The approach proposed here is the blended SC of a single input as outlined in Fig. 2. This architecture consists of a Human Agent (HA) or operator, an Electronic Agent (EA) with three distinct functions, and a controlled system. The operator issues input command $\theta_0$ via a human interface device such as a joystick and perceives the machine response $x$ through sensory feedback. A high-level EA modifies the original operator command through some general functional relationship to $\delta$. Here the functional relationship is a simple summation $\theta = \theta_0 + \delta$. The command perturbation is calculated by the blended shared control module and may be a function of several terms including the original input $\theta$ as calculated by the optimization module, the original input command $\theta_0$, and machine response $x$. The optimized command $\theta$ is determined by dynamic models of the system, the feedback $x$, and a set of data $C$ consisting of constraints and objective functions which are specific to the particular task being completed by the operator. The constraints and objective function are determined by the task identification module of the robotic controller.

There are several areas in this process that can enable a positive synergy between the EA and HA, as there are capabilities of a HA (e.g., reasoning, safety awareness, robustness, “ideal” cost function) and complimentary attributes of an EA (e.g., incorporation of complex system models, numerical capacity to solve those models, storage of much expert knowledge). These synergies of the blended SC will nominally be leveraged to increase utility of the overall process. However, there are several stages in this process which may result in dis-utility and hence must be considered. Such unresolved issues include the effects of conflicting objectives between the EA and the HA (e.g., one agent values minimum time while the other wishes minimum energy), and under which conditions can it be shown that the machine response when subject to a modified command is less costly than the response to the original command. As a first approach in illustrating this process, in the next section we present a formulation of a single-input example.
A. Shared control scheme

In this section we formulate the blended SC law for a system with a single control input $\theta$. The difference of the operator’s command $\theta_0$ and the optimal command $\tilde{\theta}$ calculated by the electronic agent is

$$\Delta = \theta_0 - \tilde{\theta}$$

(1)

The optimization as calculated by the SC module depends on the plant models and a cost function internal to the EA. A command perturbation $\delta$ calculated by the SC module is added to the operator command giving

$$\theta = \theta_0 + \delta$$

where $\theta$ is the control input to the machine. Designing the command perturbation is a major subject of our forthcoming research into blended SC. In the case of a pursuit or interception problem, for example, the perturbation may be a function of any number of terms including an operator setpoint, distance to target, time on target, or $\Delta$. For example, choosing $\delta = -e\Delta$ gives

$$\theta = \theta_0 - e\Delta$$

(2)

with the blended shared control parameter $e \in [0, 1]$. Note, when $e = 0$ the system is under manual control (i.e. $\theta = \theta_0$) and when $e = 1$ the system is fully autonomous (i.e. $\theta = \tilde{\theta}$). Varying $e$ on the interval $[0, 1]$ thus gives a continuum between full automation and full manual control.

III. ZERMELO’S PROBLEM: TIME-OPTIMAL NAVIGATION

A classic optimal control problem known as Zermelo’s Problem is useful for studying the proposed SC law because of its known closed-form solution [14]. The choice of Zermelo’s problem as a prototype was arbitrary, aside from its convenience. Our purpose is to study the interaction between human and electronic agents during SC; not to promote improved ship navigation. In addition, the task–minimize the transit time to the origin–is easily defined and explained to a human operator.

In Zermelo’s problem a ship (modeled as a particle) travels with constant speed $V$ relative to the water while navigating a region of strong currents. The captain modulates the ship’s heading $\theta$ to minimize travel time to the origin. The equations describing the optimal path for the case of linearly varying current velocity are [14]

$$\dot{x} = V \cos \theta + u(y)$$

and

$$\dot{y} = V \sin \theta$$

(3)

and

$$\dot{\theta} = -\cos^2 \theta \frac{du}{dy}$$

(4)

where $\theta$ is the ship’s heading measured from the $x$-axis, $(x, y)$ are its coordinates, and $u = Vy/h$ is the velocity of the current. The initial value of $\theta$ is chosen so that the path passes through the origin. For the linearly varying current strength considered here, the optimal steering angle can be related to the ship position through a system of implicit feedback equations [14]

$$\frac{y}{h} = \sec \theta_f - \sec \theta$$

and

$$\frac{x}{h} = \frac{1}{2} [\sec \theta_f (\tan \theta_f - \tan \theta) - \tan \theta (\sec \theta_f - \sec \theta)] + \frac{1}{2} \log \frac{\tan \theta_f + \sec \theta_f}{\tan \theta + \sec \theta}.$$  

(5)

Solutions to the above equations are plotted in Fig. 3. The blended SC of Zermelo’s problem is achieved by using the single input control law in (2). The control designer has freedom in selecting the particular form of the SC parameter $e$; suppose $e$ is selected to be

$$e = \max(0, 1 - \frac{d}{d_0}) \cdot \max(0, 1 - (\Delta/\Delta_0)^2).$$  

(6)

Fig. 4 shows plots of $e$ for the parabolic form (6). This particular form in (6) allows manual operation if the ship is greater than distance $d_0$ from the origin or if the input command deviates from the optimal by greater than $\Delta_0$. Thus, the blended SC relinquishes control authority to the operator in the presence of large “errors” between the operator input and the optimal input calculated by the electronic agent. The operator (rather than a complicated automatic controller requiring many feedback measurements) provides for the robustness and corrective action of the
system. Choosing $e$ as such is a first attempt at increasing overall system robustness by resolving the conflict that may arise between the independent agents; such conflict may stem from inaccurate models plant or environment models, dissimilar cost functions used, or different goals altogether between the operator and robot.

IV. EVALUATION OF SHARED CONTROL

Here we describe the experimental setup for evaluating the blended SC. An operator views a monitor (Fig. 5) depicting a ship moving in a simple virtual reality (VR) environment with dynamics governed by (3). A green ring represents the origin to which the operator is instructed to navigate as quickly as possible. A green sphere is drawn in front of the ship to represent the present heading $\theta$. Two static arrows illustrate the direction of the flow on either side of the origin.

The operator displaces the joystick an angle $\phi_0$ to command a ship heading $\theta_0$ through the relation

$$\theta_0 = \alpha \int \phi_0 dt$$

where $\alpha$ is a constant for tuning the snappiness of the ship response to changes in joystick angle. A deadzone on the joystick input angle $\phi_0$ is applied in software to prevent unintentional drift of the ship’s heading.

A. Description of control types evaluated

Five varieties of control were studied in this experiment and are summarized next.

**Manual control (MC):** Implemented by setting $e = 0$ in (2), thus the HA is in full control of the ship heading giving $\theta = \theta_0$. No cues are displayed to the operator, besides the standard VR interface. This control is used as a baseline for determining operator performance in absence of supplementary information or aiding controls.

**Heads up display (HUD):** The HA has manual control of the ship ($e = 0$ so $\theta = \theta_0$). A red dot (as in Fig. 5b) is displayed and represents the optimal ship heading calculated by the EA. The operator is instructed before the experiment to align the green heading indicator dot with the red HUD marker. This control provides a baseline to determine the maximum operator capabilities, i.e., the capability the operator would have if the optimal solution was known to the operator. The HUD is a form of indirect SC, in the sense defined in the Introduction.

**Haptic feedback (Haptic):** This is a second type of indirect SC. The HA has manual control of the ship. A Saitek Cyborg EVO Force joystick displays a restoring force $F = \min(1, \max(|\Delta|/\Delta_{max}, 0) F_{max} \cdot \text{sgn}(\Delta))$. This resulting force pushes the operator’s hand in a direction that causes $\theta$ to approach $\theta_0$. For example, if $\Delta \leq 0$ then the joystick applies a force to the right, thus cueing the operator to decrease angle $\phi_0$. The particular values used were $\Delta_{max} = \pi/2$, $F_{max} = 2.1$ Newtons (measured at the joystick palm grip). The haptic feedback is motivated by the master/apprentice SC techniques proposed for surgery training [13], and was also chosen to compare to the experiments in [3], [15] where the operator chooses how to respond to haptic cues on a steering wheel.

**Shared control, heading (SC2):** The HA and EA share control of the ship heading through the relation $\theta = \theta_0 - e\Delta$, with $e = \max(0, 1 - \frac{d}{\Delta_{max}}) \cdot \max(0, 1 - (|\Delta|/\Delta_{max})^2)$ as in Fig. 4. No additional cues are displayed to the operator. The particular values during the experiment were $d_0 = 25$, $\Delta_0 = 3\pi/4$.

**Shared control, rate (SCJS):** Here, the original joystick input angle $\phi_0$ is modified by the EA giving an effective joystick input angle of $\phi = \phi_0 + \delta_\theta \cdot u(\delta_\phi, \phi_0)$, where

$$\delta_\phi = \begin{cases} -\phi_0/2 & \text{for } |\Delta| \leq \theta_{th}, \\ -k \cdot \text{sgn}(\Delta) & \text{otherwise} \end{cases}$$

and

$$u(x, y) = \begin{cases} 1 & \text{if } \text{sgn}(x) = \text{sgn}(y), \\ 0 & \text{otherwise} \end{cases}$$
Hence, the human and electronic agents share control of the rate at which the ship’s commanded heading changes. No additional cues are displayed to the operator. $(\theta_{th} = \pi/12, k = 0.5)$.

The difference between SC2 and SCJS is subtle: in SC2 the operator’s intended ship heading $\theta_0$ is perturbed by the EA, whereas in SCJS the intended joystick angle $\phi$ is perturbed.

B. Effect of shared control on minimum time-to-go

Let $T(x)$ be the minimum time-to-go at the location $x = [x, y]^T$, that is, the time to reach the origin assuming the ship starts at $x$ and follows the time-optimal path. It can be shown that

$$T(x) = h/V(\tan \theta(x) - \tan \theta_f(x))$$

where $\theta$ and $\theta_f$ are implicit functions of $x$ from (5). Consider the case $\theta = \theta_0 = \bar{\theta} + \Delta$ so the ship heading is manually controlled by the operator at location $x$ and for a length of time $dt$. Then after time $dt$ the minimum time-to-go will be

$$T_{MC} = T(x + f(x, \bar{\theta} + \Delta) dt)$$

where $f(x, \theta)$ is the vector form of equations of motion (3) and $\Delta$ is as in (1). If, on the other hand, the heading is under the SC law in (2) then the minimum time-to-go after time $dt$ can be written as

$$T_{SC} = T(x + f(x, \bar{\theta} + (1 - e)\Delta) dt).$$

While not shown here for succinctness, the function $T(x + f(x, \theta) dt)$ is convex in the variable $x$ (holding all other variables constant) for all $dt > 0$. Thus, for $e \in [0, 1]$ and any $x$

$$T_{SC} \leq T_{MC}$$

as illustrated in Fig. 6, where we have plotted $T(x + f(x, \theta) dt)$ for $x = [10, 12]^T$ and $dt = 0.01$. The minimum time-to-go using SC never exceeds the time with manual control. For a certain operator input $\theta$ at $x$, the minimum time-to-go with blended SC will never be strictly worse then that with manual control. Obviously, for other systems where the cost function is not convex, the blended SC may result in greater cost than manual control alone, as the EA may push the HA commands to a higher cost. Also, it is assumed the operator input at $x$ is independent of the type of control active, so we assumed that the operator command is not a function of the control law. Finding ways to settle these issues is the subject of our ongoing research.

C. Experimental procedure

Before the experiment, the operator is allowed five practice runs starting from various locations in the field. During these runs the HUD control is active to provide instruction on navigating the currents. Each of the experimental trials begin with the ship at one of three locations: $(12, 12), (12, -12)$, and $(0, 17)$. The constants are $h = 4$ and $V = 2$. The operator triggers a start button on the joystick and the simulation proceeds in real time with one of the five control laws active. The trial concludes when the operator navigates within $d = 1.5$ of the origin. At no time during the experiment is the operator explicitly informed which of the control laws is active; in cases when sensory cues are displayed, the operator is not told the intended meaning of the cue. The starting locations and controller orders are randomized for each operator. To partially balance learning effects the operator will experience each controller type once (but in a random order) before a type is repeated. Each operator visits each location exactly three times for each controller during the experiment, totaling 45 trials per participant.

V. RESULTS

Eight computer literate participants volunteered for the experiment. Results summarizing the performance of all operators are summarized in Fig. 7. The times are normalized with respect to the optimal time to origin from each location, then averaged among all operators for each controller. Error bars denote 95% confidence intervals. For each controller, at each location, $N=24$. The optimal times to origin are 14.97 s, 7.43 s, and 18.47 s respectively for starting locations $(12, 12), (12, -12)$, and $(0, 17)$. The mean HUD controller times were very consistent and only marginally exceeded the optimal time, as expected, presumably because the tracking skill of the operators was sufficient to track the displayed optimal command. While the HUD control type produces superior results in this case, it may be impractical in reality considering the special hardware required and the cognitive attention/distraction that may be introduced to the HA. In contrast, the blended SC methods require only a way of modifying the operator input based on the intended task and the machine state, both of which may be estimated in practice via the sensed inputs alone. The completion times of the other controllers show more variation than HUD; however, both of the blended SC approaches generally surpassed the performance under manual control.

A fair criticism of blended SC is that the HA (who, out of habit, may be very aware of a particular machine feel) cedes too much authority to the EA. This may at best lead to a benign sense that the machine is not responding in a manner
consistent with operator expectations, and, at worst, lead to the machine failing to respond to an operator’s safety-based evasive maneuvers.

To test for loss of control in this single-input example, four additional trials (two with MC, two with SC2) with each operator are performed starting from (15, 0) with a barrier intentionally placed to occlude the optimal path as in Fig. 8; hence the electronic agent tries to cause the operator to hit the barrier while the operator is instructed to avoid it. The operator performance with barriers present was 19.1 s and 19.8 s, respectively for MC and SC2; however, the data lacked sufficient statistical significant to clearly deem one approach superior to the other. Traversing the optimal path from (15, 0) to the origin in absence of the barrier takes 16.0 s; but the optimal path which avoids the barrier was not calculated. More significant was the fact that under both manual and SC, only two trials among all experimental subjects resulted in collision with the barrier. No operator affirmed a feeling of loss of control when queried about navigating around the barrier.

VI. CONCLUSION

A proposed structure for blended shared control (SC) of a system with a single input was presented. We investigated the blended SC for a class of problems (which includes Zermelo’s navigation problem) having a well-defined task and a closed-form optimal solution which was globally convex in the input variable influenced by the SC. Further, the human agent and electronic agent had equivalent cost functions. For this class of problems, initial evidence indicates that the blended SC approach is superior to purely manual control in the problem considered here. Indirect SC including visual and haptic feedback results in lower task completion times than blended SC, but requires both active attention from the operator and additional hardware to implement.

There are many issues to be studied before applying this approach to more complex problems or multi-input systems. In this case, the convexity of the problem becomes critical, as we must ensure that the perturbed command is not more costly than the original. Hence, efficient methods to verify the (at least local) convexity of practical multi-dimensional optimization problems are needed. Another softer unresolved issue involves the effects of conflicting objectives arising from mis-identified tasks or inaccurate estimations of the optimal solution.

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