Mode Switch Assistance to Maximize Human Intent Disambiguation

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***Abstract*—In this paper, we develop an algorithm for intent inference via goal disambiguation with a shared-control assistive robotic arm. Assistive systems are often required to infer human intent and this usually becomes a bottleneck for providing assistance quickly and accurately. We introduce the notion of *inverse legibility* in which the human-generated actions are legible enough for the *robot* to infer the human intent confidently and accurately. The proposed disambiguation paradigm seeks to elicit legible control commands from the human by selecting control modes that *maximally disambiguate* between the various goals in the scene. We present simulation results which look into the robustness of our algorithm and the impact of the choice of confidence functions on the performance of the system. Our simulation results suggest that the disambiguating control mode computed by our algorithm produces more intuitive results when the confidence function is able to capture the "directedness" towards a goal. We also present a pilot study that explores the efficacy of the algorithm on real hardware. Preliminary results indicate that the assistance paradigm proposed is a promising approach in decreasing task effort (number of mode switches) across interfaces and tasks.**

I. Introduction

Assistive and rehabilitation devices such as powered wheelchairs, robotic arms and myoelectric prostheses play an important role in the lives of people with motor impairments. These devices help to increase their ability to perform activities of daily lives and reduce their dependence on caretakers, and are crucial to revolutionizing the way they interact with society. As the field of assistive robotics progresses rapidly, the devices themselves become more capable and dextrous—and as a result also more complex, high dimensional and harder to control.

The common paradigm for control of such high-dimensional devices has the human directly control the motion via a control interface. Furthermore, the more severe a person's motor impairment, the more limited are the control interfaces available for use (is this ok?). These interfaces (for example, a switch-based head array and Sip-N-Puff) are lower in dimensionality and bandwidth, and usually require more mode switches for successful task completion. Therefore, we have a conundrum, in which sophisticated assistive devices that requires complex control strategies are paired with users whose abilities to control them are deteriorating.

Due to the dimensionality mismatch between the control interface and the robotic device, control interfaces operate in *modes* which correspond to different partitions of the control space. Typically, the more limited the control interface is, the greater number of modes there are. In order to have full control of the robot the user will have to switch between the different partitions and this is known as *mode switching or modal control* [19, 16].

It has been established that mode switching is expensive and as a result task performance is degraded. Furthermore, it adds to the cognitive and physical burden as each of these mode switches requires the user to shift their attention from the task to performing the mode switch. The introduction of *shared autonomy* to these systems helps to alleviate and address some of these issues by letting the system take responsibility of task execution partially, thereby reducing the human effort in achieving a goal.

For any assistive autonomy, the system typically needs an idea of what it is the human is trying to do—either by explicit indication from the user of the task or goal [6], or by inferring the human's intent from their control signals and/or sensor data. The question of intent inference is key. In this paper, we develop an assistance paradigm that helps with intent inference, by selecting the control mode in which robot motion will *maximally disambiguate* human intent. The faster the autonomy is able to disambiguate intent, the earlier the robot is able to provide autonomy assistance—leading ideally to fewer mode switches and less burdensome executions.

In many shared-control systems, the assistance provided by the robot is regulated by the robot's ability to estimate user intent confidently and accurately, and it is very unlikely that the robot will be able to determine this with a 100% accuracy. Therefore in the literature to date, the factor dictating how much control lies with the robot versus with the human is usually a function of a confidence metric. This confidence metric is a measure of the robot's estimate that a particular goal in the environment is indeed the user's intended goal; ie., it is an estimate of human intent. Confidence functions usually depend on the human control command, the autonomous policy, robot pose, goal locations, *et cetera*. This implies that human control actions can potentially have a direct impact on

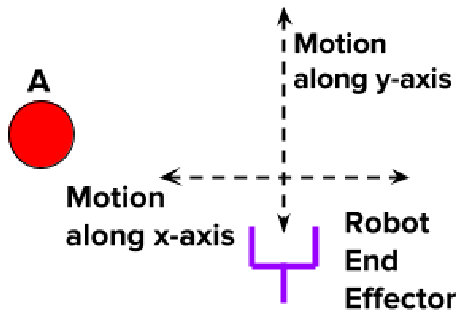

Fig. 1. Illustration of goal disambiguation along various control dimensions. A and B indicate two point goal locations. The robot end effector is at location C. Any motion of the end effector along the y-axis will not help the system to disambiguate between the two goals; that is, the motion is not legible. However, motion along the x-axis allows the goal to be inferred immediately based on the direction in which the robot moves.

the confidence measure.

The concept of *legibility* is typically used in the domain of Human-Robot Interaction (HRI) as applied to robot motion. A *legible* motion in this context is one which will help the observer (usually the human) decipher the intent behind the robot's action more *quickly* and *confidently*. However, it can be the case that certain actions *by* the human might carry more information than others and better express the human's intent, which can then help the robot to draw useful and correct inferences more easily. Therefore, in this paper we propose a paradigm of *inverse legibility* in which the roles are switched and the human-generated actions *help the robot* to infer human intent confidently and accurately.

Consider the example illustrated in Figure 1. In this example, a human control command issued along the x dimension is more *intent expressive* and helps the robot to provide the right kind of assistance quickly and confidently. With the disambiguation assistance scheme developed in this work, we hope to elicit more legible human control commands by placing the user control in those modes with *maximum disambiguation* between the various goals in the scene.

In Section II we present an overview of relevant research in the area of shared control in assistance systems focusing on mode switching, legibility and synergies in HRI. Section III describes the mathematical formalism for the algorithm and the metric used for goal disambiguation. The simulation results are presented in Section IV. The pilot study experimental setup, methods and results are discussed in Section V, followed by conclusions in Section VI.

II. RELATED WORKS

Shared-control assistance paradigms help to offload cognitive and physical burden [20] without requiring the user to relinquish complete control, and are usually preferred over fully autonomous assistive robotic systems for reasons of both robustness and user satisfaction. How exactly should sharing happening between the human and robot control will greatly benefit from intent inference mechanisms in the shared-control architectures. Methods for intent inference have been extensively studied by roboticists and cognitive scientists alike and can be broadly classified into two categories namely, model-based and heuristic-based [4]. In model-based approach the agent is typically modeled as a POMDP that acts according to a policy that maps states to actions. In such settings intent inference reduces to solving the inverse problem of computing the posterior distribution over mental states conditioned on observed actions (Bayesian Inference) [2, 3]. On the other hand, heuristic-based approaches rely on low-level motion cues [5], biological signals [7] etc., and seek to find direct mappings between the raw signals and the underlying intention and is usually computationally less expensive than model-based approaches. The results of intent inference engines can then be utilized to determine the appropriate kind of assistance required for a particular scenario; e.g., mode-switch assistance.

Herlant *et al.* [11] assesses the difficulties faced by users when they operate assistive devices using *modal control*. In their work they report that a significant number of users found *mode switching* to be slow and burdensome. The cognitive burden of shifting focus (*task switching*) from the task at hand to mode switches can result in a significant decrease in task performance regardless of the control modality [15]. A time-optimal mode switch assistance paradigm evaluated on a simulated 2D robot provides insight into the fact that even a simple time-optimal automatic mode switching system can significantly improve user satisfaction while maintaining the quality task performance [11]. Another study [10] found that it is not always the case that users are trying to optimize for time or effort during task execution. However, our present system therefore does not make *a priori* assumptions regarding the optimizing principles at work when a user operates a robot.

The legibility and predictability of robot motion *to the human* have been thoroughly investigated [8], and different methods for generating legible robot motion have been proposed by Holladay *et al* [12]. We apply similar concepts of legibility to the *human control* commands, such that the intent expressed in the human command is clear *to the robot*. Our assistance scheme is intended to bring out a more legible intent-expressive control command from the human, so that the autonomy is able to infer the correct goal more confidently. As long as the confidence measure used to disambiguate between candidate goals captures the predictable aspect of human-generated robot motion, our proposed disambiguation assistance will place user control in that mode which can provide maximal goal disambiguation and improved legibility.

Eliciting legible commands from the user can also be thought of as an information acquisition problem. Information acquisition in robotic systems, primarily in the context of generating optimal control for mobile robotic sensing systems have been widely studied. A typical approach is to model the problem as an optimal control problem with an associated reward structure that reflect some measure of information gain [1]. Miller et al. have also formulated the problem of information gathering as maximizing ergodicity of a robot's

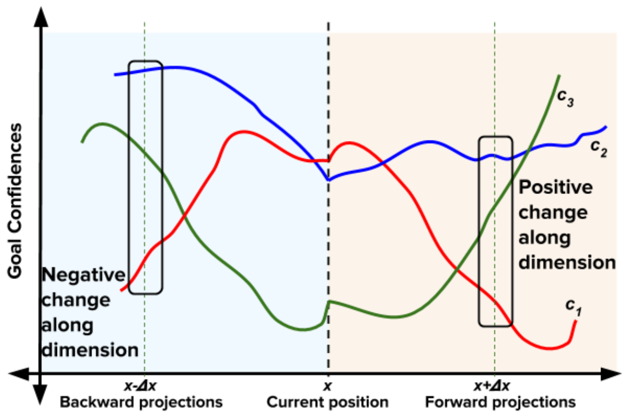

Fig. 2. Illustration of change in confidence with movement along a single control dimension. The region accessible from position x due to positive and negative motion is shaded beige and light blue respectively. Note the discontinuity in the confidences at the current position.

trajectory with respect to an underlying information density map [13, 14]. In their work, the information density map is computed by evaluating the expected value of the Fisher information, which is the amount of information a single measurement reveals at a location.

Also related to our work is the idea of mutual cooperation between humans and robots, and the underlying synergies that are crucial for successful human-robot interaction. The commonplace notion in human-robot interaction, and especially in assistive robotics, is that "help" is provided solely by the robot. In addition to eliciting more legible motion from the human, we also seek to exploit the underlying synergies in human-robot interaction to faciliate more seamless and efficient task execution. From the robot's perspective the key concept behind our algorithm is the idea of *"Help Me, Help You"*—that is, if the human can "help" the robot by providing more legible control commands, then the robot in turn can assist the human even more effectively. This concept has been explored by Goodfellow *et. al* [9] for developing user interfaces that overcome the communication bottleneck that exists between robots and people by accounting for the constrained capabilities of a robot. Sorokin *et al.* [18] proposes a framework for *"people helping robots helping people"* in which humans provide semantic information and judgments about the environment to the robot which then utilizes them to improves its own capabilities. Rosenthal *et al.* [17] proposes a *symbiotic* human robot interaction scheme which aims to overcome perceptual and cognitive limitations that robots might encounter while still allowing the robots to help humans as well.

III. ALGORITHM DESIGN

This section describes the algorithm that is used to compute the control mode with maximum goal disambiguation, thereby eliciting the most legible control command from the human. Section III-A outlines the mathematical notation used in the paper and Section III-B discusses various confidence functions. Section III-C describes the different considerations that inform the confidence disambiguation metric. The details of the underlying shared control system is also described briefly in this Section III-D.

A. Notation

Let $\mathcal{G}$ be the set of all candidate goals in the scene with $n_g = |\mathcal{G}|$ and let g^i refer to the i^{th} goal where $i \in [1, 2, \ldots, n_g]$. The set of goals results in an associated set of confidences (discussed in Section III-B) denoted as $\mathcal{C}$, where c^i refers to the individual confidence associated with goal g^i. Let $\mathcal{K}$ be the control space in which the robot operates and k^i refer to an individual control dimension where $i \in [1, 2, \ldots, n_k]$. The cardinality of $\mathcal{K}$ depends on the robotic platform; for example, for a smart wheelchair $n_k = 2$ whereas for a 6 DOF robotic arm $n_k = 6$.

For control purposes, the set $\mathcal{K}$ is partitioned into subsets known as *modes*. Let $\mathcal{M}$ refer to the set of all modes that the control space $\mathcal{K}$ is partitioned into with $n_m = |\mathcal{M}|$. The number of modes (n_m) is specific to the control interface and mapping to $\mathcal{K}$. Furthermore, let m^i refer to the i^{th} mode where $i \in [1, 2, \ldots, n_m]$.

Another quantity of interest is the spatial gradient of individual goal confidences for motions along the different control dimensions. More specifically, the gradient will be denoted by $\frac{\partial c}{\partial x_k}$, where $c \in \mathcal{C}$ and x_k is the component of robot's position ($\boldsymbol{x}$?) along control dimension k[1]. Furthermore, since the confidence function, in general, can assume drastically different values upon moving in positive and negative directions along a given control dimension, the positive and negative gradients are explicitly denoted as $\frac{\partial c}{\partial x}^+$ and $\frac{\partial c}{\partial x}^-$ respectively. The formalism developed in Section III-C is agnostic to a particular form of confidence function. Additionally, an analytical closed-form expression for the gradient might not always be available as the confidence functions need not be continuous and differentiable. Even when available, due to the complexity of the confidence measure such an expression might be expensive to compute. Therefore in our work, the gradient is numerically approximated.

We define a *disambiguation* metric, $D_k \in \mathbb{R}$ for each control dimension $k \in \mathcal{K}$, which is a function of c and $\frac{\partial c}{\partial x}$. Analogous to the gradients, we explicitly define disambiguation metrics for both positive and negative motion directions as D_k^+ and D_k^- respectively. We further define a disambiguation metric $\boldsymbol{D}_m \in \mathbb{R}$ for each control mode $m \in \mathcal{M}$. The disambiguation metric $\boldsymbol{D}_m$ is a measure of how legible the user commands would be if the user were to control the robot in mode m. The higher the value, the easier it will be for the system to infer the human's intent.

B. Confidence function

The choice of confidence function is entirely up to the system designer and numerous options exist. An example of

[1]The subscript k will be dropped from x_k for brevity in notation.

a simple proximity-based confidence function is

$$c(\boldsymbol{x}, \boldsymbol{x_g}) = \max(0, 1 - \frac{\|\boldsymbol{x} - \boldsymbol{x}_g\|}{R})$$

where $\boldsymbol{x}$ is the current position of the robot, $\boldsymbol{x}_g$ is the location of goal g, R is the radius of a sphere beyond which the confidence is always 0 and $\|\cdot\|$ is the Euclidean norm. We refer to this confidence function as **C1**. However, this confidence measure ignores all cues regarding human intent present in the control command itself. Therefore a better choice of confidence function should try to capture the "directedness" of the human control command towards a goal. One option is

$$c(\boldsymbol{x}, \boldsymbol{x_g}, \boldsymbol{u}_h) = \boldsymbol{u}_h \cdot (\boldsymbol{x}_g - \boldsymbol{x})$$

where $\boldsymbol{u}_h$ is the human control command. We refer to this confidence function as **C2**. **C1** and **C2** can be combined into a single function to capture both proximity to and directedness towards a goal.

Furthermore, the control signal from the robot autonomy is generated by a function $f_r(\cdot) \in \mathcal{F}_r$,

$$\boldsymbol{u}_r \leftarrow f_r(\boldsymbol{x})$$

where $\mathcal{F}_r$ is the set of all control behaviors corresponding to different tasks. The algorithm proposed in this paper requires that the confidence measures varies as a function of $\boldsymbol{x}$, so that $\frac{\partial c}{\partial x}$ is well-defined and exists. The specific form of the confidence function and the autonomous robot policy generator will be discussed in Section III-D.

C. Disambiguation metric

The disambiguation metric D_k encodes different aspects of how the goal confidences change upon moving (either in the positive or negative direction) along control dimension k. Figure 2 is an illustrative example which shows how goal confidences can vary as a function of position along a control dimension. A proper design of D_k should take into account both immediate as well as long term benefits of moving in k and combine them into one metric. We identify four important considerations (components?) to inform the design of D_k.

1) Separation in confidences: A good measure for evaluating the confidence disambiguation potential of a control dimension is to compute the *separation*, Λ_k, in goal confidences. At any point in space this can be computed as the *sum of pairwise distances* between the n_g confidences. Since we are interested in the separation after a small change in position (due to user-initiated robot motion), we can sample the confidence function at $x \pm \Delta x$ and use the sampled values to compute Λ_k, where Δx is a small change along the control dimension. Thus,

$$\Lambda_k = \sum_{p=1}^{n_g} \sum_{q=p}^{n_g} |c^p_{\delta_x} - c^q_{\delta_x}|$$

where δ_x indicates $x + \Delta x$ or $x - \Delta x$ depending on the direction of perturbation and $|\cdot|$ denotes the absolute value. If the confidence functions depend on the user control command ($\boldsymbol{u}_h$) then during the sampling procedure the value of $\boldsymbol{u}_h$ is assumed to be one that would make the robot position from go from x to $x \pm \Delta x$ in unit time.

2) Max of confidences: The maximum of the goal confidences is a good measure of the system's overall certainty in accurately estimating human intent. A higher maximum implies that the robot has an even better idea of and is fairly sure of what the human is trying to do. The max (Γ_k) is computed as

$$\Gamma_k = \max_{1 \leq i \leq n_g} c^i_{\delta_x}$$

3) Difference between largest confidences: Since it is possible to have multiple[2] highly confident goals, accurate disambiguation also benefits from a large separation between the first and second most confident goals. This difference is denoted by Δ_k and is computed as

$$\Delta_k = \max(\mathcal{C}_k) - \max(\mathcal{C}_k \setminus \max(\mathcal{C}_k))$$

where $\mathcal{C}_k$ is the set of all the projections of goals confidences along control dimension k.

4) Gradients: The propensity for change and information gain upon the continuation of motion along control dimension k is encoded in the gradients $\frac{\partial c}{\partial x}\ \forall\ c \in \mathcal{C}$. The greater the difference between the gradients of individual confidences c, the greater will they deviate from each other. Instead of using closed-form analytical gradients, we approximate the gradients using forward and backward differences. Therefore,

$$\frac{\partial c}{\partial x} \approx c_{\delta_x} - c_x$$

where c_x denotes the confidence at location x. In order to quantify the "spread" of gradients we define a quantity Υ_k which is computed as

$$\Upsilon_k = \sum_{p=1}^{n_g} \sum_{q=p}^{n_g} \left| \frac{\partial c^p}{\partial x} - \frac{\partial c^q}{\partial x} \right|$$

Putting it all together: Λ_k, Γ_k, Δ_k and Υ_k are then combined to compute D_k as

$$D_k = \underbrace{\boldsymbol{w} \cdot (\Lambda_k \cdot \Gamma_k \cdot \Delta_k)}_{\text{short term}} + \underbrace{(1 - \boldsymbol{w}) \cdot \Upsilon_k}_{\text{long term}} \tag{1}$$

where $\boldsymbol{w}$ controls the relative contribution of immediate and the long term benefit and is task-specific. Equation 1 actually is computed twice, once in each of the positive ($\delta_x = x + \Delta x$) and negative directions ($\delta_x = x - \Delta x$), and the results are then summed. Once the disambiguation metric D_k for each control dimension k is computed, the disambiguation metric $\boldsymbol{D}_m$ for control mode m is calculated as

$$\boldsymbol{D}_m = \sum_k D_k\ \forall\ k \in m$$

Lastly, the control mode with highest disambiguation capability $\boldsymbol{m}^*$ is given by

$$\boldsymbol{m}^* = \operatorname*{argmax}_m \boldsymbol{D}_m$$

[2]Note that confidences are not normalized, since we do care about more than just their relative magnitudes as in bullet 2.

and the control dimension with highest disambiguation capability $\boldsymbol{k}^*$ is given by

$$\boldsymbol{k}^* = \underset{k}{\operatorname{argmax}}\, D_k$$

Disambiguation mode $\boldsymbol{m}^*$ is the mode that the algorithm chooses *for* the human to better their intent. Any subsequent control command issued by the user in $\boldsymbol{m}^*$ is likely to be more legible due to maximal goal confidence disambiguation.

D. Blending paradigm

The proposed disambiguation assistance paradigm augments a blending-based shared control system, in which the final control command issued to the robot is a blended sum of the human control command and an autonomous robot policy. The blending factor (α) is a function of the system's confidence.

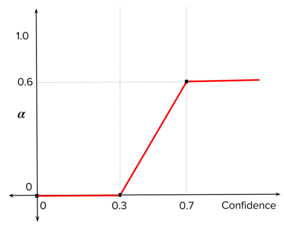

Fig. 3. A prototypical arbitration function.

Let $\boldsymbol{u}_{r,g}$ be the autonomous control policy associated with goal g. The final control command $\boldsymbol{u}$, issued to the robot is then given as

$$\boldsymbol{u} = \alpha \cdot \boldsymbol{u}_{r,\boldsymbol{g}^*} + (1-\alpha)\cdot \boldsymbol{u}_h$$

where $\boldsymbol{g}^*$ is the most confident goal.

The robot control command $\boldsymbol{u}_{r,g}$ is generated using a simple potential field based dynamical system which is defined in all parts of the state space. Every goal g is associated with a potential field P_g which treats g as an attractor and all the other goals in the scene as repellers. For potential field P_g, the attractor velocity is given by

$$\dot{\boldsymbol{x}}_{attract} = \boldsymbol{x}_g - \boldsymbol{x}$$

where $\boldsymbol{x}_g$ is the location of g. The repeller velocity is given by

$$\dot{\boldsymbol{x}}_{repel} = \sum_{i\in\mathcal{G}\setminus g} \frac{\boldsymbol{x}-\boldsymbol{x}_i}{\eta(\|\boldsymbol{x}-\boldsymbol{x}_i\|^2)}$$

where $\dot{\boldsymbol{x}}$ indicates the velocity of the robot in the world frame. Therefore,

$$\boldsymbol{u}_{r,g} = \dot{\boldsymbol{x}}_{attract} + \dot{\boldsymbol{x}}_{repel}$$

Additionally, P_g operates in full six dimensional Cartesian space and treats position and orientation as independent potential fields.

In our implementation confidence c_g is computed as

$$c_g(\boldsymbol{x}, \boldsymbol{u}_h, \boldsymbol{u}_{r,g}) = \boldsymbol{u}_h^{trans}\cdot(\boldsymbol{x}_g-\boldsymbol{x})^{trans} + \boldsymbol{u}_h^{rot}\cdot \boldsymbol{u}_{r,g}^{(rot)} \quad (2)$$

where $trans$ refers to the translational and rot refers to the rotational parts of the entire control space. The first term captures the "directedness" of the human control command towards the goal g and the second term captures the alignment between the human control command and the autonomous robot policy in the rotational parts of the state space respectively. The blending factor α is a parameterized function of the confidence and is depicted in Figure 3.

Best control dimension distribution				
Confidence Function	**X**	**Y**	**Z**	**NULL**
C1	579	615	446	360
C2	1711	93	196	0

TABLE I
BEST CONTROL DIMENSION DISTRIBUTION FOR TWO DIFFERENT CONFIDENCE FUNCTIONS.

IV. SIMULATION RESULTS

We first evaluate the disambiguation system for correctness within a simulated environment.

A. *Choice of Confidence Functions*: Since D_k and $\boldsymbol{D}_m$ are evaluated using c and $\frac{\partial c}{\partial x}$, they are both indirectly functions of $\boldsymbol{x}$. The choice of confidence functions can also greatly affect the computation of $\boldsymbol{k}^*$ and $\boldsymbol{m}^*$. In order to quantify the differences between different choices for confidence functions, we performed simulations in which $\boldsymbol{k}^*$ was computed at 2000 uniformly sampled points in the workspace of the robot, approximated as a $1.2\times0.6\times0.7m^3$ volume in front of the robot. **C1** and **C2** were chosen as the confidence functions and the goal configuration was same as in Figure 5 (middle column). Since the target orientations are same for all goals, disambiguation only happens in the translational dimensions and therefore is reduced to a three-dimensional problem. The value of R in **C1** was set as $0.3m$.

Figure 4 shows the results of the simulation. It is clear that the choice of confidence function changes the preferred control dimensions in the workspace quite significantly.

More importantly, it also sheds light on the efficacy of a confidence function in capturing human intent properly. For the goal distribution used in the simulation, the goal positions are spread out maximally along the x and z axes. Intuitively the system will be able to quickly infer the human's intent if the human control command is either along the x or the z axes. However, this requires that the confidence function indeed captures the directedness of the human control command.

Table I reports the number of times the algorithm picked each of the three control dimensions, for each confidence function. **C1** often was unable to capture the human intuition properly. Furthermore, **C1** had "null" spaces where all confidences were identically equal to zero and therefore disambiguation was not possible.

By contrast, with **C2** the algorithm identified x as the preferred dimension 1711 out of 2000 samples, and z in 196 of the remaining 289 samples, which indicates that the confidence function along with our algorithm was able to select the disambiguating dimensions over 95% of the time. The algorithm picked y only when the robot directly in front of a goal.

n_g	3	4	5
Accuracy%	89.24	87.09	86.11

TABLE II
DISAMBIGUATION ACCURACY FOR OFF-AXIS MOTIONS

B. *Characterization of Simplifying Assumption:* In our algorithm, the computation of $\boldsymbol{D}_m$ is simplified and only considers

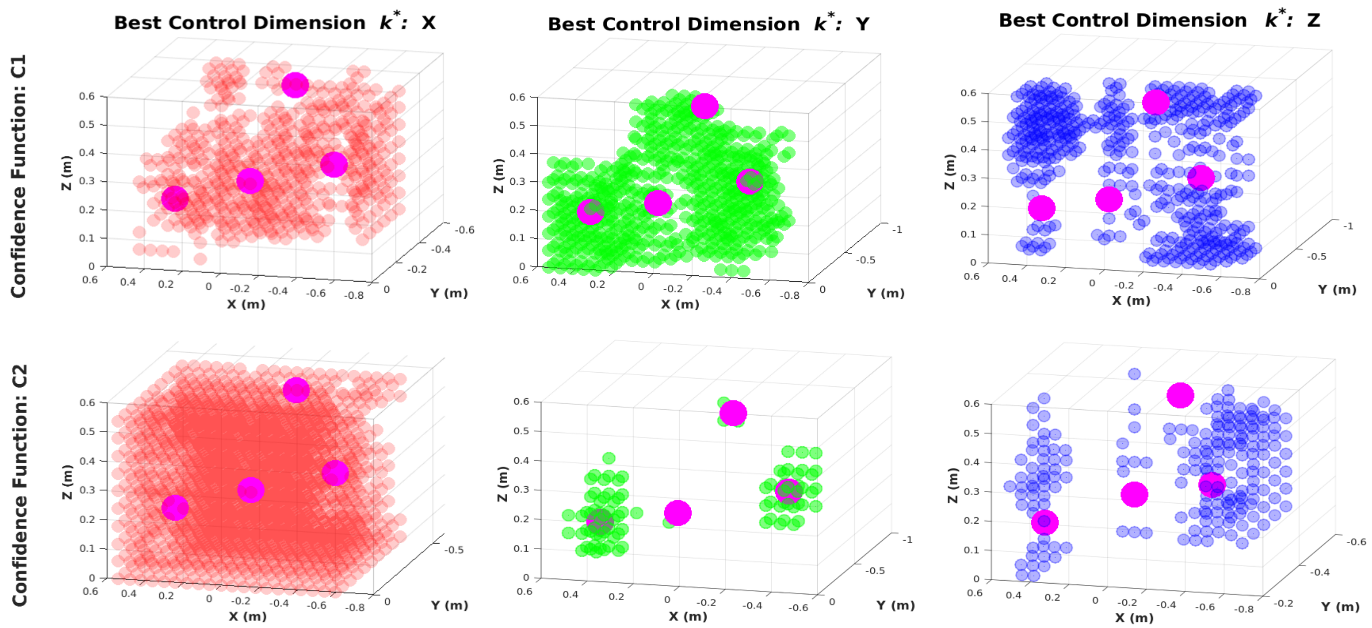

Fig. 4. Top row: Best control dimensions for confidence measure **C1**. Bottom row: Best control dimensions for confidence measure **C2**. Left column: $\boldsymbol{k}^*$ is X. Middle Column: $\boldsymbol{k}^*$ is Y. Right Column: $\boldsymbol{k}^*$ is Z. Magenta spheres indicate the goal locations.

motion projected along perpendicular vectors: the axes of each dimension k_i of mode m. However, in reality the user can generate a control command in any arbitrary direction within the control mode, and so the robot can move along any vector spanned by the control dimensions in m. In order to assess whether the simplification was indeed sufficient to characterize the disambiguation capability of being in a mode, we performed simulations in which $\boldsymbol{m}^*$ was computed for 500 uniformly spaced locations in the robot workspace. At each of those points, 100 random control commands that are feasible in $\boldsymbol{m}^*$ were generated and applied to perturb the robot. Finally, at each of these perturbed positions the best control mode was once again computed.

If the best mode in the perturbed position was the same mode as $\boldsymbol{m}^*$, then the simplification did not adversely affect the identification of the disambiguating mode. Table II summarizes the number of times a match occurred for different configurations of the workspace (number of goals). While the simplification holds for $85 - 90\%$ of off-axis motions, we do observe a trend where performance drops as the number of goals increase. Intuitively this makes sense because disambiguation between goals will become harder as the number of goals increase.

C. *Discussion (part 1)*: Our simulation results indicate that the choice of confidence function has a huge impact on the performance of our algorithm. Confidence functions that encode the "directedness" present in the human control command are likely to be more effective in capturing human intent. Moreover, the algorithm can be used to pre-compute the best modes ahead of time and can be used as a look-up table during task execution for automated mode switching. A single mode switch assistance provided at the beginning of the trial might not be enough to and therefore automated mode switching during task execution will be critical to improve task performance especially for more limited interfaces.

V. PILOT STUDY

We next investigate the use and utility of our disambiguation approach in a pilot study. Four subjects participated in the pilot study, (3 male, 1 female), and all were lab members.

A. Hardware

The experiments were performed using real hardware and simulated versions of the MICO robotic arm (Kinova Robotics, Canada), which is a 6 DOF robotic arm specifically designed for assistive purposes. The software system was implemented using the Robot Operating System (ROS) and data analysis was performed using MATLAB.

The human control command $\boldsymbol{u}_h$ was captured using two different control interfaces: 2-axis joystick and a head array shown in Figure 6. A 2-axis joystick generates continuous signals and is capable of controlling a maximum of two control dimensions at a time. Control modes can be accessed using the buttons on the interface. On the other hand, head array is a switch-based discrete teleoperation device. Head array consists of three switches to be operated by the back and sides of the head. When used for controlling a robotic arm, the switch at the back is used to cycle between the modes and the switches on the left and right side are to control the motion of the end-effector in the positive and negative direction along a control dimension. The control interface signals are mapped to Cartesian velocities of the end effector

Fig. 5. Pilot study tasks performed by the subjects. *Left to right:* Simple Reaching (*R*), Reaching with Same Grasp (*RsG*), Reaching with Different Grasp (*RdS*).

of the robot. Additionally, the interfaces can also be used to request mode switch assistance. In using two interfaces, we hope to observe an increase in task effort for the head array due to the limited bandwidth and discrete nature of the control signals.

Control Mappings		
Mode	**Head Array**	**Joystick**
1	v_x	v_x, v_y
2	v_y	v_x, v_z
3	v_z	ω_z, ω_y
4	ω_z	ω_x
5	ω_y	—
6	ω_x	—

Fig. 6. A 2-axis joystick (left) and switch-based head array (center) and their operational paradigms (right)

B. Assistance Paradigms

Three kinds of mode switching paradigms were evaluated. Note that the blending assistance (as described in Section III-D) was always running for all three paradigms. This implies that if the intent inference improves as a result of disambiguation, more assistance will be provided by the robot, resulting in improved task performance.

Manual: In this paradigm, the trial starts in a randomized initial mode and during task execution the user manually performs all subsequent mode switches.

Disambiguation: In this paradigm, the disambiguation system is activated right at the beginning of a trial. The algorithm identifies the "best mode" $\boldsymbol{m}^*$ and starts the trial in mode $\boldsymbol{m}^*$. All subsequent mode switches are performed manually by the user. Furthermore, the user is required to first move in the selected mode before manually switching the mode.

On Demand: In this paradigm, the user can request a mode switch assistance at any time during task execution. This paradigm is exploratory and seeks to find underlying patterns in assistance request behavior.

C. Task Descriptions

Three tasks were developed for our pilot study (Figure 5).

Simple Reaching (R) : The user operates the robotic arm to perform simple reaching motions to three different goal locations. This is a training task and the primary purpose is to get the user accustomed to the operation of the interfaces, the blending-based assistance and the experiment protocol.

Reaching with Same Grasp (RsG) : The user teleoperates the robotic arm using ~~both control interfaces~~ either one of the control interfaces to perform reaching motions towards one of four objects on the table with the same grasp orientation.

Reaching with Different Grasp (RdG): This is a more difficult task that *RsG* in which the user operates the robot to perform reaching motions to one of five objects in the scene with different grasp orientations.

Data from both tasks (*RsG* and *RdG*) were pooled for analysis purposes.

D. Pilot Study Protocol and Metrics

Protocol: A within-subject study was conducted using a full factorial design in which the manipulated variables are the tasks, control interfaces and assistance paradigms. Each task consisted of two phases.

In phase I, each user performed the task using both interfaces under *Manual* and *Disambiguation* paradigms. The trials were balanced and the control interfaces and the paradigms were randomized to eliminate ordering effects. The starting positions of the robot were also randomized to avoid biases. Three trials were collected for each permutation of manipulated variables. In phase II, the user performed the same task using both interfaces using the *on-demand* paradigm and two trials were collected for each task-interface combination.

Metrics: A number of objective metrics were evaluated during this pilot study. *Task completion time* is the amount of time a user spends in accomplishing a task. *Mode switches* refer to the number of times the user switched between various modes while performing the task and is an indicator of effort.

E. Pilot Study Results

An improvement in task performance in terms of a decrease in the number of mode switches was observed across both interfaces. Statistical significance in Figure 7 is determined by two-sided Wilcoxon Rank-Sum Test, where (*) indicates $p < 0.05$ and (***) indicates $p < 0.001$.

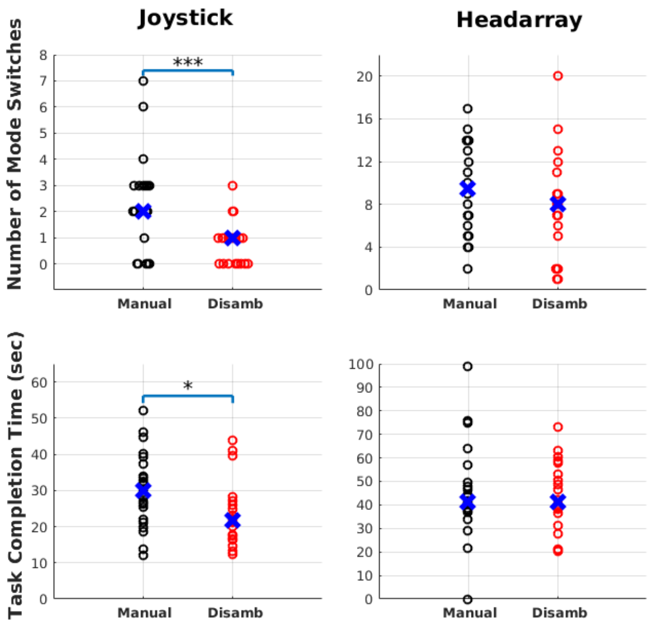

Fig. 7. Comparison of Disambiguation and Manual paradigms. Operation using a joystick (left column) and head array (right column) interfaces. Evaluation of mode switches (top row) and completion time (bottom row). ✖ indicates the median.

Mode Switches: Figure 7 (top row) reveals the general trend of a decrease in the number of mode switches across both. However, the difference in the number of mode switches was statistically significant only when using the joystick. This indicates that upon starting in a mode identified by the algorithm, the number of subsequent mode switches performed by the user was reduced.

Task Completion Time: In Figure 7 (bottom row), a statistically significant decrease in task completion times between *Manual* and *Disambiguation* paradigms was observed when using the joystick. The task completion times were comparable between the two paradigms when using the head array. This can be possibly explained by the fact that a *single* mode switch assistance at the beginning of the trial probably did not have a measurable impact in reducing the subsequent number of mode switches needed when using a head array and therefore required the same amount of time.

On–Demand: The number of disambiguation requests for each task-interface combinations is reported in Table III. Although the subjects demonstrated a wide range of disambiguation request behaviors, we were able to observe a general trend of an increase in disambiguation requests with an increase in task difficulty. This shows that users were keen to explore the *on-demand* option when the tasks became more difficult.

F. Discussion

Currently the algorithm assumes that at any point in the workspace all the goals in the scene are equally likely. However, in the real scenario, the user usually has an idea of what goal s/he is going for. Therefore, it might be useful to bias the

	Joystick		Head Array	
SubID	*RsG*	*RdG*	*RsG*	*RdG*
H1	1	0	5	6
H2	1	1	3	6
H3	2	2	4	5
H4	2	5	17	7

TABLE III
NUMBER OF DISAMBIGUATION REQUESTS

computation of the "best control mode" by looking for cues in the past history of the robot trajectory and control commands such that the control mode chosen will always be useful for the human in reaching the goal s/he has in mind. This will also likely improve the robustness and result in higher user acceptance. Secondly, the algorithm only tries to maximize the utility value *for* the robot. Concepts from decision theory can be used to augment the current framework to also include a utility function *for* the human. A more extensive user study with motor-impaired subjects will be conducted in the future to evaluate the utility value of the disambiguation assistance system and further explore and understand the disambiguation request patterns of users.

VI. CONCLUSIONS

In this paper, we have presented an algorithm for disambiguation assistance with a shared-control robotic arm. We also introduced the notion of *inverse legibility*, in which the human-generated actions are legible enough *for* the robot to infer the human intent confidently and accurately. The goal of the algorithm developed in this paper is to seek legible control commands from the human by placing the control in those modes able to *maximally disambiguate* between the various goals in the scene. Moreover, preliminary pilot study results indicated that the disambiguation paradigm proposed in this work is a promising approach in decreasing task effort (number of mode switches) across interfaces and tasks. Our simulation work evaluated the robustness of the algorithm and the impact of different confidence functions on intent disambiguation. In our future work, informed by our pilot studies we plan to enhance our algorithm, to improve task performance and extend the framework into an automated mode switch assistance system.

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