Projection-Aware Task Planning and Execution for Human-in-the-Loop Operation of Robots in a Mixed-Reality Workspace

Tathagata Chakraborti Sarath Sreedharan Anagha Kulkarni Subbarao Kambhampati

***Abstract*— Recent advances in mixed-reality technologies have renewed interest in alternative modes of communication for human-robot interaction. However, most of the work in this direction has been confined to tasks such as teleoperation, simulation or explication of individual actions of a robot. In this paper, we will discuss how the capability to project intentions affect the *task planning* capabilities of a robot. Specifically, we will start with a discussion on how projection actions can be used to reveal information regarding the future intentions of the robot at the time of task execution. We will then pose a new planning paradigm – *projection-aware planning* – whereby a robot can trade off its plan cost with its ability to reveal its intentions using its projection actions. We will demonstrate each of these scenarios with the help of a joint human-robot activity using the HoloLens.**

I. Introduction

Effective planning for human robot teams not only requires the ability to interact with the human during the plan execution phase but also the capacity to be "human-aware" during the plan generation process as well. Prior work has underlined this need [1] as well as explored ways to exchange [2] information in natural language during interaction with the human in the loop. This is also emphasized in the *Roadmap for U.S. Robotics* [3] – *"humans must be able to read and recognize robot activities in order to interpret the robot's understanding"*. However, the state of the art in natural language considerably limits the scope of such interactions, especially where precise instructions are required. In this paper, we present the case of wearable technologies (e.g. HoloLens) for effective *communication of intentions* during human-in-the-loop operation of robots. Further, we show that such considerations are not confined to the plan execution phase only, *but can guide the plan generation process itself* by searching for plans that are easier to communicate.

In our proposed system, the robot projects its intentions as *holograms* thus making them directly accessible to the human in the loop, e.g. by projecting a pickup symbol on a tool it might use in future. Further, unlike in traditional mixed reality projection systems, the human can directly interact with these holograms to make his own intentions known to the robot, e.g. by gazing at and selecting the desired tool thus forcing the robot to replan. To this end, we develop an alternative communication paradigm that is based on the projection of explicit visual cues pertaining to the plan under execution via holograms such that they can be intuitively understood and directly read by the human. The "real" shared human-robot workspace is thus augmented with the virtual space where the physical environment is used as a medium to convey information about the intended actions of the robot, the safety of the workspace, or task-related instructions. We call this the *Augmented Workspace*. In this paper –

- We demonstrate how the Augmented Workspace can assist human-robot interactions during *task-level* planning and execution by providing a concise and intuitive vocabulary of communication.
- In Section IV, we show how the intention projection techniques can be used to reduce **ambiguity over possible plans** during execution as well as generation.
    - In Section IV-D, we show how this can be used to realize a *first of its kind* task planner that, instead of considering only cost optimal plans in the traditional sense, *generates* plans which are easier to explicate using intention projection actions.
- In Section V, we demonstrate how the ability to project world information applies to the process of explanations to address **inexplicability of a plan** during execution.

Note that the ability to communicate information, and planning with that ability to disambiguate intentions, is not necessarily unique to mixed-reality interactions only. For example, one could use the planner introduced in Section IV-D to generate *content* for traditional speech-based interactions as well (c.f. recent works on verbalization of intentions in natural language [2], [4]). However, as demonstrated in this paper, the medium of mixed-reality provides a particularly concise and effective alternative (albeit much more limited) vocabulary of communication, especially in more structured scenarios such as in collaborative assembly.

II. Related Work

The concept of intention projection for autonomous systems has, of course, been explored before. An early attempt was made in [5] in a prototype Interactive Hand Pointer (IHP) to control a robot in the human's workspace. Similar systems have since been developed to visualize trajectories of mobile wheelchairs and robots [6], [7], which suggest that humans prefer to interact with a robot when it presents its

The authors are with the Department of Computer Science at Arizona State University, Tempe AZ USA. Contact: { tchakra2, ssreedh3, akulka16, rao } @ asu.edu

This research is supported in part by the AFOSR grant FA9550-18-1-0067, the ONR grants N00014-16-1-2892, N00014-13-1-0176, N00014-13-1-0519, N00014-15-1-2027, N00014-18-1-2442 and the NASA grant NNX17AD06G. The first author is also supported by the IBM Ph.D. Fellowship from 2016-18. We also thank Professors Heni Ben Amor and Yu "Tony" Zhang (Arizona State University) for their valuable inputs.

Parts of this project appeared in the U.S. Finals of the Microsoft Imagine Cup 2017. Details: http://www.ae-robots.com/

An extended version of this paper is available publicly at https://goo.gl/ZFGjPK.

intentions directly as visual cues. The last few years have seen active research [8], [9], [10], [11], [12], [13], [14], [15] in this area, but most of these systems were passive, non-interactive and quite limited in their scope, and did not consider the state of the objects or the context of the plan pertaining to the action while projecting information. As such, the scope of intention projection has remained largely limited. Indeed, recent works [16], [17], [18] have made the first steps towards extending these capabilities to the context of task planning and execution, but fall short of formalizing the notion of intention projections beyond the current action under execution. Instead, in this paper, we demonstrate a system that is able to provide much richer information to the human during collaboration, in terms of the current state information, action being performed as well as future parts of the plan under execution, particularly with the notion of explicating or foreshadowing future intentions.

Recent work in the scope of human-aware task and motion planning has focused on generation of legible motion plans [19], [20] and explicable task plans [21], [22] with the notion of trading off cost of plans with how easy they are to interpret for a human observer. This runs parallel to our work on planning with intention projections. Note that, in effect, either during the generation or the execution of a plan, we are, in fact, trying to optimize the same criterion. However, in our case, the problem becomes much more intriguing since the robot gets to *enforce legibility or explicability of a plan by foreshadowing of actions that have not been executed yet*. Indeed, this connection has also been hinted at in recent work [23]. *However, to the best of our knowledge, this is the first task-level planner to achieve this trade-off.*

The plan explanation and explicability process forms a delicate balancing act [24]. This has interesting implications to the intention projection ability as we demonstrate in the final section. Similarly, in [25], authors have looked at the related problem of *"transparent planning"* where a robot tries to signal its intentions to an observer by performing disambiguating actions in its plan. Intention projection via mixed-reality is likely to be a perfect candidate for this purpose without incurring unnecessary cost of execution.

III. Preliminaries of Task Planning

A Classical Planning Problem [26] is a tuple $\mathcal{M} = \langle \mathcal{D}, \mathcal{I}, \mathcal{G} \rangle$ with domain $\mathcal{D} = \langle F, A \rangle$ - where F is a set of fluents that define a state $s \subseteq F$, and A is a set of actions - and initial and goal states $\mathcal{I}, \mathcal{G} \subseteq F$. Action $a \in A$ is a tuple $\langle c_a, \mathit{pre}(a), \mathit{eff}^{\pm}(a) \rangle$ where c_a is the cost, and $\mathit{pre}(a), \mathit{eff}^{\pm}(a) \subseteq F$ are the preconditions and add/delete effects, i.e. $\delta_{\mathcal{M}}(s, a) \models \bot \textit{ if } s \not\models \mathit{pre}(a); \textit{ else } \delta_{\mathcal{M}}(s, a) \models s \setminus \mathit{eff}^{-}(a) \cup \mathit{eff}^{+}(a)$ where $\delta_{\mathcal{M}}(\cdot)$ is the transition function. The cumulative transition function is $\delta_{\mathcal{M}}(s, \langle a_1, a_2, \ldots, a_n \rangle) = \delta_{\mathcal{M}}(\delta_{\mathcal{M}}(s, a_1), \langle a_2, \ldots, a_n \rangle)$.

Note that the "model" $\mathcal{M}$ of a planning problem includes the action model *as well as the initial and goal states of an agent*. The solution to $\mathcal{M}$ is a sequence of actions or a (satisficing) *plan* $\pi = \langle a_1, a_2, \ldots, a_n \rangle$ such that $\delta_{\mathcal{M}}(\mathcal{I}, \pi) \models \mathcal{G}$. The cost of a plan π is $C(\pi, \mathcal{M}) = \sum_{a \in \pi} c_a$ if $\delta_{\mathcal{M}}(\mathcal{I}, \pi) \models \mathcal{G}$; ∞ otherwise. The cheapest plan $\pi^* = \arg\min_{\pi} C(\pi, \mathcal{M})$ is the (cost) optimal plan with cost $C^*_{\mathcal{M}}$.

In addition, *"projection actions"* in the mixed reality workspace are annotations on the environment that can include information on the state of the world or the robot's plans – these can reveal information regarding the robot's future intentions, i.e. goals or plans. In this work, we assume a very simple projection model based on the truth value of specified conditions in parts of the plan yet to be executed –

An Action Projection AP is defined as a mapping $u : [0 \ldots |\pi|] \times A \mapsto \{\texttt{T}, \texttt{F}\}$ indicating $\exists\ j \geq i$ where $a_j \in \pi$ iff $u(i, a_j) = \texttt{T}$ – i.e. existence or membership of an action a_j in the rest of the plan starting from the current action a_i.

A State Value Projection SVP is defined as a mapping $v : F \times A \mapsto \{\texttt{T}, \texttt{F}\}$ so that there exists a state in the state sequence induced by the sub-plan starting from a_i where the state variable $f \in F$ holds the value $v(f, a_i)$, i.e. $\exists\ s' : \delta_{\mathcal{M}}(s, \pi') \models s'$ where s is the current state and π' is the sub-plan $(\pi)_{k=i}^{k \leq |\pi|}$ and $f \in s'$ iff $v(f, a_i) = \texttt{T}$.

This engenders a restricted vocabulary of communication between the human and the robot. However, it only allows for disambiguation of plans based on membership of actions (AP) and not their sequence, and also only the occurrence of a state variable value (SVP) in the future with no information as to when. Further, not all actions or state values can be projected, i.e. the APs and SVPs available to the robot cover only a subset of all the actions and state values that can be communicated. Thus plans may not be always possible to disambiguate with only these projection actions. Even so, we will demonstrate in this paper how the robot can use this vocabulary to effectively explicate its intentions to the human in the loop in a variety of situations. In the following sections, we will discuss how the robot can determine *when* to deploy *which* of these projections for this purpose.

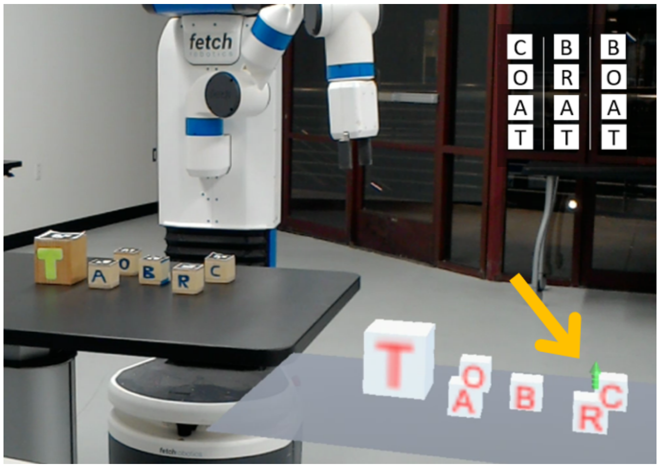
IV. Projections for Ambiguous Intentions

In this section, we will concentrate upon how projection actions can resolve ambiguity with regards to the intentions of a robot in the course of *execution* of a task plan.

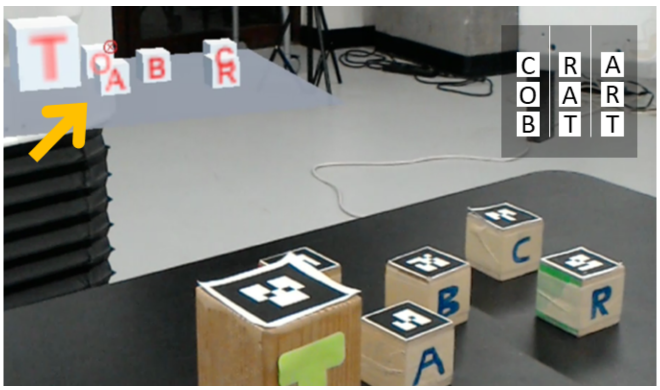
A. Projection-Aware Plan Execution

The first topic of consideration is the projection of intentions of a robot with a human *observer* in the loop.

Illustrative Example. Consider a robot involved in a block stacking task (Figure 1a). Here, the robot's internal goal is to form the word `BRAT`. However, given the letters available to it, it can form other words as well – consider two more possible goals `BOAT` and `COAT`. As such, it is difficult to say, from the point of view of the observer, by looking at the starting configuration, which of these is the real outcome of the impending plan. The robot can, however, at the start of its execution, choose to indicate that it has planned to pick up the block R later (by projecting a bobbing arrow on top of



(a) The robot projects (AP) a green arrow on R to indicate a pickup that is part of an optimal plan to only one of its possible goals.



(b) The robot inverts the projection context and shows (SVP) which block is *not* going to be available using a red cross on A.

Fig. 1: Projection-Aware Plan Execution for human observer and human-in-the-loop scenarios.

it), thereby resolving this ambiguity. A video demonstration can be viewed at `https://goo.gl/SLgCPE`.

Note that directly displaying the actual goal – here, the final word – is not possible in general across different domains since these holograms have to be constructed separately for each goal. Thus, the projections are tied to the robot's capabilities (e.g. pick-up) instead. Further, and perhaps more importantly, we are trying to disambiguate plans as well and revealing the goal does not in general achieve that purpose.

A Projection-Aware Plan Execution Problem PAPEP is defined as the tuple $\Phi = \langle \pi, \Pi, \{AP\}, \{SVP\} \rangle$ where π is the robot's plan up for execution, Π (which includes π) is the set of possible plans it can execute. $\{AP\}$ and $\{SVP\}$ are the set of action and state value projections available.

The solution to Φ is a composite plan $\pi^c \circ \pi$ where $\pi^c \subseteq \{AP\} \cup \{SVP\}$ are the projection actions that disambiguate the plans at the time of execution. We compute this using the concept of resource profiles, as introduced in [27]. Informally, a *resource* [27] is defined as any state variable whose binary value we want to track. We will use this concept to tie each action or state value projection action to a single resource variable, whose effect can be monitored. For example, a `not-clear` predicate will indicate that a block is in use or not available while an action that produces or negates that predicate – e.g. `pick-up` can be similarly tracked through it. This mapping between projection actions and the corresponding resource variables is domain-dependent knowledge that is provided.

A Resource Profile $\mathcal{R}^\pi$ induced by a plan π on a resource r is a mapping $\mathcal{R}^\pi : [0 \ldots\ |\pi|] \times r \mapsto \{0, 1\}$, so that r is *locked* by π at step i if $\mathcal{R}^\pi(r, i) = 1$ and it is free otherwise.

A Cumulative Resource Profile $\mathbb{R}^\Pi$ induced by a *set* of plans Π on a resource r is a mapping $\mathbb{R}^\Pi$: $[0 \ldots\ \max_{\pi \in \Pi} |\pi|] \times r \mapsto [0, 1]$, so that r is *locked* with a probability $\mathbb{R}^\Pi(r, i) = \sum_{\pi \in \Pi} \mathcal{R}^\pi(r, i) \times P(\pi)$, where $P(\pi)$ is the prior probability of plan π (assumed uniform).

The set of projection actions π^c in the solution π to the PAPEP Φ are found by computing –

$$\arg\min_r \sum_i \mathcal{R}^\pi(r, i) \times \mathbb{R}^\Pi(r, i) \tag{1}$$

Thus, we are post-processing to minimize the conflicts between the current plan and the other possible plans, so that the projection actions that are tied to the resources with the minimal conflicts give us the most distinguishing projection.

B. Projection-Aware Human-in-the-Loop Plan Execution

In the previous example, we confined ourselves to situations with the human only as the observer. Now, we consider a situation where both the human and the robot are involved in task planning in a collaborative sense, i.e. both the human and the robot perform actions in a joint plan to achieve their goals which may or may not be shared.

Illustrative Example. Going back to the running example of the block stacking task, now consider that the robot and the human both have goals to make a three letter word out of ART, RAT and COB (as seen in Figure 1b). The robot has decided to make the word ART, but realizes that this leaves the human undecided on how to proceed. Thus the disambiguating projection action here includes annotating the A block with a "not available" symbol so that the only possible goal left for the human is COB. A video demonstrating this can be viewed at `https://goo.gl/SLgCPE` (same as in Section IV-A). Note that in this case the robot, in coming up with a useful projection action, has reversed the perspective from what is relevant to its own plan, to information that negates possible plans of the human in the loop.

A Projection-Aware Human-in-the-Loop Plan Execution Problem PAHILPEP is a tuple $\Psi = \langle \pi^R, \Pi^H, \mathbb{G}, \{AP\}, \{SVP\} \rangle$ where π^R and Π^H are the robot's plan and the set of possible human plans, $\mathbb{G}$ is the team goal, and $\{AP\}$ and $\{SVP\}$ are the set of action and state value projections available to the robot.

The solution to Φ is, as before, a composite plan $\pi^c \circ \pi^R$ where the projection actions are composed with the robot's component of the joint team plan, such that $\delta(\mathcal{I},\ \pi^c \circ \pi^R \circ$

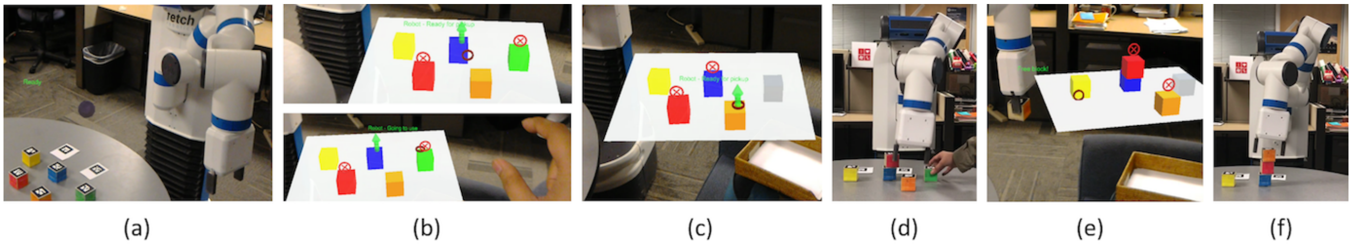


Fig. 2: Interactive execution of a plan in the Augmented Workspace - **(a)** the robot wants to build a tower of height three with blocks blue, red and green. **(b)** Blocks are annotated with intuitive holograms, e.g. an upward arrow on the block the robot is going to pick up immediately and a red cross mark on the ones it is planning to use later. The human can also gaze on an object for more information (in the rendered text). **(c)** & **(d)** The human pinches on the green block and claims it for himself. The robot now projects a faded out green block and re-plans online to use the orange block instead (as evident by pickup arrow that has shifted on the latter at this time). **(e)** Real-time update and rendering of the current state showing status of the plan and objects in the environment. **(f)** The robot completes its new plan using the orange block.

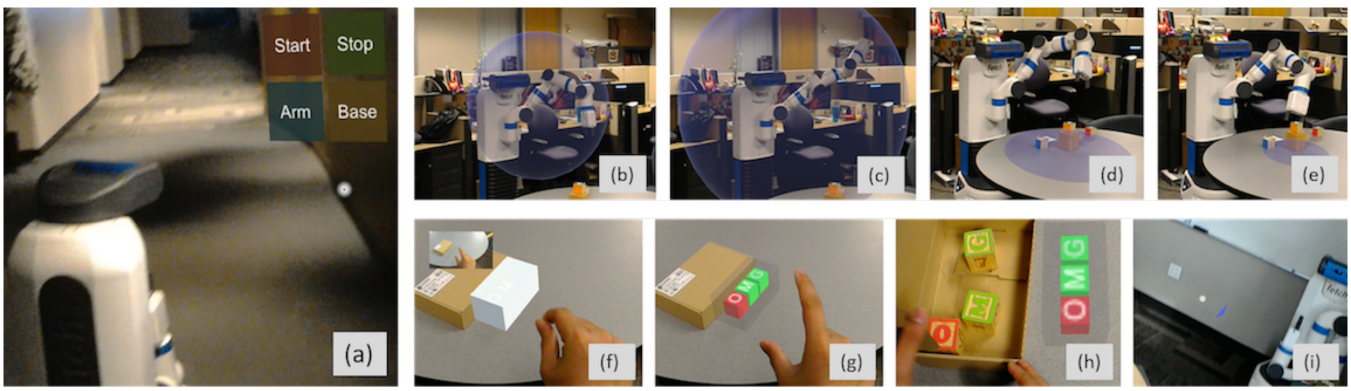


Fig. 3: Interactive plan execution using the **(a)** Holographic Control Panel. Safety cues showing dynamic real-time rendering of volume of influence **(b)** - **(c)** or area of influence **(d)** - **(e)**, as well as **(i)** indicators for peripheral awareness. Interactive rendering of hidden objects **(f)** - **(h)** to improve observability and situational awareness in complex workspaces.

$\pi^H) \models \mathbb{G}$. The set of projection actions π^c in the solution to the PAHILPEP Ψ is again found by computing –

$$\arg\max_{r} \sum_{i} \mathcal{R}^{\pi^R}(r, i) \times \mathbb{R}^{\Pi^H}(r, i) \tag{2}$$

Notice the inversion to `argmax`, since in the case of an active human in the loop, so as to provide the most pertinent information regarding conflicting intentions to the human.

Remark. Joint plans [28] to reason over different modes of human-robot interactions has been investigated before, particularly in the context of using resource profiles [27] for finding conflicts in the human's and the robot's plans. It is interesting to note the reversed dynamics of interaction in the example provided above – i.e. in [27] the resource profiles were used so that the robot could replan based on probable conflicts so as to preserve the expected plans of the human. Here, we are using them to identify information to project to the human, so that the latter can replan instead.

C. Closing the Loop – Interactive Plan Execution

Of course, it may not be possible to always disentangle plans completely towards achievement of a shared goal in a collaborative setting. Next, we show how the communication loop is closed by allowing the humans to interact directly with the holograms in the augmented workspace thereby spawning replanning commands to be handled by the robot, in the event of conflicting intentions.

1) Replanning – : In the previous examples, the robot projected annotations onto the objects it is intending to manipulate into the human's point of view with helpful annotations or holograms that correspond to its intentions to use that object. The human can, in turn, access or claim a particular object in the virtual space and force the robot to re-plan, without there ever being any conflict of intentions in the real space. The humans in the loop can thus not only infer the robot's intent immediately from these holographic projections, but can also interact with them to communicate their own intentions directly and thereby modify the robot's behavior online. The robot can also then ask for help from the human, using these holograms. Figure 2 demonstrates one such scenario. The human can also go into finer control of the robot by accessing the Holographic Control Panel, as seen in Figure 3(a). The panel provides the human controls to start/stop execution of the robot's plan, as well as achieve fine grained motion control of both the base and the arm by making it mimic the user's arm motion gestures on the MoveArm and MoveBase holograms attached to the robot.

2) Assistive Cues – : The use of AR is, of course, not just restricted to procedural execution of plans. It can also be used

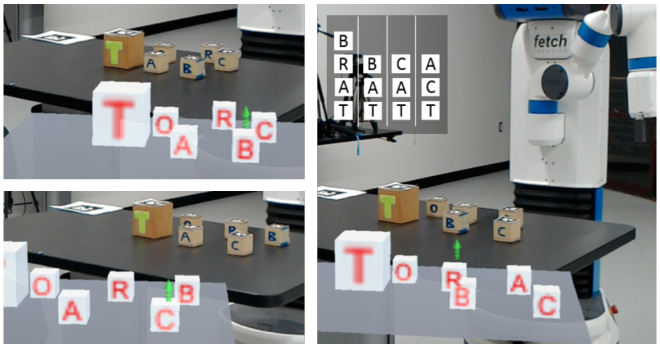


Fig. 4: Projection-aware plan generation illustrating trade-off in plan cost and goal ambiguity at the time of execution – (**top left**) generating a plan that has the most discriminating projection (green arrow on `B` – only one word `BAT` possible); when longer word `BRAT` is available – (**bottom left**) $\alpha = 100$ yields green arrow on `C` with two words `ACT` and `CAT` possible while (**right**) $\alpha = 1000$ yields green arrow on `R` with only one *but longer* word `BRAT` possible.

to annotate the collaborative workspace with artifacts derived from the current plan under execution in order to improve the fluency of collaboration. For example, Figure 3(b-e) shows the robot projecting its area of influence in its workspace either as a 3D sphere around it, or as a 2D circle on the area it is going to interact with. This is rendered dynamically in real-time based on the distance of the end effector to its center, and to the object to be manipulated. This can be very useful in determining safety zones around a robot in operation. As seen in Figure 3(f-i), the robot can also render hidden objects or partially observable state variables relevant to a plan, as well as indicators to improve peripheral vision of the human, to improve their situational awareness.

Demonstrations for Sections IV-C and IV-C.2 can be viewed at `https://goo.gl/pWWzJb`.

D. Projection-Aware Plan Generation

Now that we have demonstrated how intention projection can be used to disambiguate possible tasks at the time of execution, we ask *is it possible to use this ability to* ***generate*** *plans that are easier to disambiguate in the first place?*

Illustrative Example. Consider again the blocks stacking domain, where the robot is yet to decide on a plan, but it has three possible goals `BAT`, `CAT` and `ACT` (Figure 4). From the point of view of cost optimal planning, all these are equally good options. However, the letter `B` is in only one of the words, while the others are in at least two possible words. Thus the robot is able to *reduce the ambiguity in plans* by choosing the word `BAT` over the other options as a means of achieving the goal of making a word from the given set.

Illustrative Example. Now imagine that we have extended the possible set of words { `BAT`, `CAT`, `ACT` } with a longer word `BRAT`. The robot responds by projecting `R` and completes this longer word now, given `R` is the most discriminating action, and the possibility of projecting it ahead completely reveals its intentions **even though it involves the robot doing a longer and hence costlier plan** as seen in Figure 4. This trade-off in the cost of plans and the ambiguity of intentions forms the essence of what we refer to as *projection-aware planning*. In fact, we can show that by correctly calibrating this trade-off, we can achieve different sweet spots in how much the robot decides to foreshadow disambiguating actions. As seen in Figure 4, in cases where the action costs are relatively greater than gains due to resolved ambiguity, the robot achieves a middle-ground of generating a plan that has the same cost as the optimal plan to achieve the goal of making a word from this set, but also involves reasonable forecasting of (two) possible goals by indicating a future `pick-up` action on `C`. A video demonstrating these behaviors can be viewed at `https://goo.gl/bebtWS`.

Algorithm 1 Projection-Aware Planning Algorithm

procedure PAPP-SEARCH
Input: PAPP $\Lambda = \langle \mathcal{M}, \kappa, \{AP\}, \phi \rangle$
Output: Plan π
Procedure:
$\mathcal{A} \leftarrow \mathcal{A} \cup \{AP\}$ ▷ Add projections to action set
fringe $\leftarrow$ `Priority_Queue()`
fringe.push($\langle \mathcal{I}, \langle\rangle \rangle, 0$)
while True **do**
$\langle \widehat{S}, \hat{\pi} \rangle, c \leftarrow$ fringe.pop()
if goal check true **then** return $\hat{\pi}$ ▷ Refer to Section IV-D
else
for $a \in A$ **do**
if $\hat{s} \models pre(a)$ **then**
$\hat{s}' \leftarrow \delta(\hat{s}, a)$
fringe.push($\langle \hat{s}',\ \hat{\pi} + a \rangle,\ F(\hat{s}', a, \hat{\pi})$)

procedure F($\hat{s}', a, \hat{\pi}$)
if $a \notin \{AP\}$ **then**
return $c_a + cost(\hat{\pi})$
else
Compute $\Pi = \{delete-relaxed\ plans\ to\ \kappa\}$
$N \leftarrow 0$
for $\pi \in \Pi$ **do**
if $AP^{-1}(a) \in \pi$ **then**
$N \leftarrow N + 1$
return $\alpha(\ c_a + cost(\hat{\pi})\ ) + \beta N$ ▷ (Equation 4)

A Projection-Aware Planning Problem PAPP is defined as the tuple $\Lambda = \langle \mathcal{M}, \kappa, \{AP\}, \{SVP\} \rangle$ where $\mathcal{M}$ is a planning problem and κ is a set of disjunctive landmarks.

The solution to Λ is a plan such that –

– π achieves the goal; and
– commitments imposed by the projection actions, i.e. future state conditions indicated by SVPs or actions promised by APs (Section III) are respected.

The search for which projection actions to include is achieved by modifying a standard A* search [29] so that the cost of a plan includes actions costs as well as the cost of ambiguity over future actions (e.g. to possible landmarks) given a prefix. This is given by –

$$\alpha\ C(\hat{\pi}, \mathcal{M}) + \beta\ \mathbb{E}(\Pi, \hat{\pi}) \tag{3}$$

Here Π is a set of possible plans that the robot can pursue from the current state and $\mathbb{E}(\Pi)$ is the entropy of the probability distribution [30] over the plan set Π given the current plan prefix $\hat{\pi}$ to that state. Since a full evaluation of the plan recognition problem in every node is prohibitively expensive, we use a simple observation model where the currently proposed projection action tests *membership* of its parent action if it is an AP (or state value if it is an SVP) in a minimal delete-relaxed plan [31] to each landmark –

$$\alpha C(\pi, \mathcal{M}) + \beta \sum_{\kappa} I(a_i \in \pi - del) \qquad (4)$$

where I is the indicator function indicating if the current action a_i is part of the minimal delete-relaxed plan $\pi - del$ from the current state to each of the landmarks κ. Of course, there can be many such plans only some of which include the projection action as a necessary component. So at best, in addition to the delete relaxation, checking membership only provides a guidance (and no guarantees) to which of the possible plans can include a projection. The set of landmarks was composed of the possible words that contributed to the goal of making a valid word. The details[1,2] are provided in Algorithm 1. Notice that the indicator function only comes into play when projection actions are being pushed into the queue, thus biasing the planner towards producing plans that are easier to identify based on the projections.

V. Projections for Inexplicable Actions

In the previous section, we had focused on dealing with *ambiguity* of intentions during execution of a plan. Now we will deal with *inexplicability* of actions, i.e. how to use projection capabilities to annotate parts of the world so that a plan under execution "makes sense" to the observer.

Illustrative Example. Going back to our block stacking setting, consider a scenario where the human-in-the-loop asks the robot to make a tower of height three with the red block on top (Figure 5). Here the optimal plan from the point of view of the observer is likely to be as follows –

```
>> Explicable Plan    |  >> Robot Optimal Plan
pick-up green         |  pick-up red
stack green blue      |  put-down red
pick-up red           |  pick-up yellow
stack red green       |  stack yellow green
                      |  pick-up red
                      |  stack red green
```

However, not all the blocks (e.g. blue) are reachable, as determined by the internal trajectory constraints of the robot. So its optimal plan would instead be longer, as shown above. This plan is, of course, inexplicable if the observer knows that the robot is a rational agent, given the former's understanding of the robot model. The robot can chose to mitigate this situation by annotating the unreachable blocks as *"not reachable"* as shown in Figure 5. A video demonstration can be seen at `https://goo.gl/TRZcW6`.

The identification of projection actions in anticipation of inexplicable plans closely follows the notion of multi-model

[1]We currently handle only APs in the solution to a PAPP. Also, the number of APs in a solution were restricted to a maximum of two to three due to the time consuming nature of computing Π. This can be very easily sped up by *precomputing the relaxed planning graph*.

[2]Note that to speed up search we used "outer entanglement" analysis [32] to prune unnecessary actions for the blocks stacking domain.

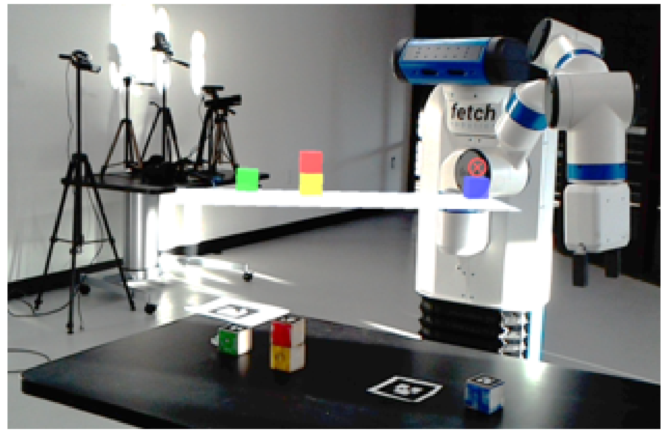


Fig. 5: The human has instructed the robot to make a tower of height 3 with the red block on top. Since the blue block is not reachable it has to unstack red in order to achieve its goal. This is a suboptimal plan to the observer who may not know the robots internal trajectory constraints and that the blue block in unreachable. The robot thus decides to project a red error symbol on the blue block indicating it is not reachable. The optimal plans in both models now align.

explanations studied in [26]. The inexplicability of actions can be seen in terms of differences in the model of the same planning problem between the robot and the human in the loop, as opposed to the examples previously where coordination was achieved with respect to aligned models.

A Multi-Model Planning Problem (MMP) is the tuple $\Gamma = \langle \mathcal{M}^R, \mathcal{M}^R_h \rangle$ where $\mathcal{M}^R = \langle D^R, \mathcal{I}^R, \mathcal{G}^R \rangle$ and $\mathcal{M}^R_h = \langle D^R_h, \mathcal{I}^R_h, \mathcal{G}^R_h \rangle$ are respectively the planner's model of a planning problem and the human's understanding of it.

In our block stacking domain, multiple models are spawned due to internal constraints of the robot that the human may not be aware of (e.g. reachability) while the world model (i.e. how the world works - the robot has to pick up and object to put it down, etc.) is shared across both the models. As these models diverge, plans that are optimal in the robot's model may no longer be so in the human's and thus become *inexplicable*. The robot can mitigate these situation by generating *multi-model explanations* [33] –

A Multi-Model Explanation is a solution to an MMP in the form of a model update to the human so that the optimal plan in the robot's model is now also optimal in the human's updated model. Thus, a solution to Γ involves a plan π and an explanation $\mathcal{E}$ such that –

(1) $C(\pi, \mathcal{M}^R) = C^*_{\mathcal{M}^R}$;
(2) $\widehat{\mathcal{M}}^R_h \longleftarrow \mathcal{M}^R_h + \mathcal{E}$; and
(3) $C(\pi, \widehat{\mathcal{M}}^R_h) = C^*_{\widehat{\mathcal{M}}^R_h}$.

We use the same to generate content for the explanations conveyed succinctly through the medium of mixed reality, as described in the illustrative example above.

VI. Conclusion

In conclusion, we showed how an augmented workspace may be used to improve collaboration among humans and robots from the perspective of task planning. This can be either via post-processing its plans during the interactive plan execution process where the robot can foreshadow future actions to reveal its intentions, or during search during the *projection-aware* plan generation process where the robot can trade-off the ambiguity in its intentions with the cost of plans. Finally, we showed how explanatory "dialogs" with the human as a response to inexplicable plans can be conducted in this mixed-reality medium as well.

Such modes of interaction open up several exciting avenues of future research. Particularly, as it relates to task planning, we note that while we had encoded some of the notions of ambiguity in the planning algorithm itself, the vocabulary of projections can be much richer and as such existing representations fall short of capturing these relationships (e.g. action `X` is going to happen 3 steps after action `Y`). A holographic vocabulary thus calls for the development of representations – PDDL3.x – that can capture such complex interaction constraints modeling not just the domain physics of the agent but also its interactions with the human. Further, such representations can be *learned* to generalize to methods that can, given a finite set of symbols or vocabulary, compute domain independent projection policies that decide what and when to project to reduce cognitive overload on the human.

Finally, in recent work [34], we looked at how the beliefs and intentions of a virtual agent can be visualized for transparency of its internal decision-making processes – we refer to this as a process of *"externalization of the brain"* of the agent. Mixed-reality techniques can play a pivotal role in this process as we demonstrate in [35]. Indeed, interfacing with virtual agents embody many parallels to gamut of possibilities in human-robot interaction [36].

Video Demonstrations. Demonstrations of all the use cases in the paper can be viewed at `https://goo.gl/Gr47h8`. The code base for the projection-aware plan generation and execution algorithms are available at `https://github.com/TathagataChakraborti/ppap`.

REFERENCES

[1] E. Karpas, S. J. Levine, P. Yu, and B. C. Williams, "Robust execution of plans for human-robot teams." in *ICAPS*, 2015.

[2] S. Tellex, R. Knepper, A. Li, D. Rus, and N. Roy, "Asking for help using inverse semantics," in *RSS*, 2014.

[3] H. I. Christensen, T. Batzinger, K. Bekris, K. Bohringer, J. Bordogna, G. Bradski, O. Brock, J. Burnstein, T. Fuhlbrigge, R. Eastman, *et al.*, "A Roadmap for US Robotics: From Internet to Robotics," 2009.

[4] V. Perera, S. P. Selvaraj, S. Rosenthal, and M. Veloso, "Dynamic Generation and Refinement of Robot Verbalization," in *RO-MAN*, Columbia University, NY, August 2016.

[5] S. Sato and S. Sakane, "A human-robot interface using an interactive hand pointer that projects a mark in the real work space," in *ICRA*, vol. 1. IEEE, 2000, pp. 589–595.

[6] A. Watanabe, T. Ikeda, Y. Morales, K. Shinozawa, T. Miyashita, and N. Hagita, "Communicating robotic navigational intentions," in *IROS*. IEEE, 2015, pp. 5763–5769.

[7] R. T. Chadalavada, H. Andreasson, R. Krug, and A. J. Lilienthal, "That's on my mind! robot to human intention communication through on-board projection on shared floor space," in *ECMR*, 2015.

[8] S. Omidshafiei, A.-A. Agha-Mohammadi, Y. F. Chen, N. K. Ure, J. P. How, J. Vian, and R. Surati, "Mar-cps: Measurable augmented reality for prototyping cyber-physical systems," in *AIAA ARC*, 2015.

[9] S. Omidshafiei, A.-A. Agha-Mohammadi, Y. F. Chen, N. K. Ure, S.-Y. Liu, B. T. Lopez, R. Surati, J. P. How, and J. Vian, "Measurable augmented reality for prototyping cyberphysical systems: A robotics platform to aid the hardware prototyping and performance testing of algorithms," *IEEE Control Systems*, vol. 36, no. 6, pp. 65–87, 2016.

[10] J. Shen, J. Jin, and N. Gans, "A multi-view camera-projector system for object detection and robot-human feedback," in *ICRA*, 2013.

[11] K. Ishii, S. Zhao, M. Inami, T. Igarashi, and M. Imai, "Designing laser gesture interface for robot control," in *INTERACT*, 2009.

[12] P. Mistry, K. Ishii, M. Inami, and T. Igarashi, "Blinkbot: look at, blink and move," in *UIST*. ACM, 2010, pp. 397–398.

[13] F. Leutert, C. Herrmann, and K. Schilling, "A spatial augmented reality system for intuitive display of robotic data," in *HRI*, 2013.

[14] M. Turk and V. Fragoso, "Computer vision for mobile augmented reality," in *Mobile Cloud Visual Media Computing: From Interaction to Service*, 2015.

[15] I. Maurtua, N. Pedrocchi, A. Orlandini, J. de Gea Fernández, C. Vogel, A. Geenen, K. Althoefer, and A. Shafti, "Fourbythree: Imagine humans and robots working hand in hand," in *ETFA*. IEEE, 2016, pp. 1–8.

[16] R. S. Andersen, O. Madsen, T. B. Moeslund, and H. B. Amor, "Projecting robot intentions into human environments," in *RO-MAN*, 2016, pp. 294–301.

[17] Y. R. H. B. A. H. Ganesan, R.; Rathore, "Mediating human-robot collaboration through mixed reality cues," in *IEEE Robotics and Automation Magazine*, 2018.

[18] T. Chakraborti, S. Sreedharan, A. Kulkarni, and S. Kambhampati, "Alternative modes of interaction in proximal human-in-the-loop operation of robots," *CoRR*, vol. abs/1703.08930, 2017, uISP 2017 and ICAPS 2017 Demo Track.

[19] A. Dragan and S. Srinivasa, "Generating legible motion," in *Proceedings of Robotics: Science and Systems*, 2013.

[20] A. Dragan, S. Bauman, J. Forlizzi, and S. Srinivasa, "Effects of robot motion on human-robot collaboration," in *HRI*, 2015.

[21] Y. Zhang, S. Sreedharan, A. Kulkarni, T. Chakraborti, H. H. Zhuo, and S. Kambhampati, "Plan Explicability and Predictability for Robot Task Planning," in *ICRA*, 2017.

[22] A. Kulkarni, T. Chakraborti, Y. Zha, S. G. Vadlamudi, Y. Zhang, and S. Kambhampati, "Explicable Robot Planning as Minimizing Distance from Expected Behavior," *CoRR*, vol. abs/1611.05497, 2016.

[23] Z. Gong and Y. Zhang, "Robot signaling its intentions in H-R teaming," in *HRI Workshop on Explainable Robotic Systems*, 2018.

[24] T. Chakraborti, S. Sreedharan, and S. Kambhampati, "Balancing Explanations and Explicability in Human-Aware Planning," in *AAMAS Extended Abstract*, 2018.

[25] A. M. MacNally, N. Lipovetzky, M. Ramirez, and A. R. Pearce, "Action selection for transparent planning," *AAMAS*, 2018.

[26] T. Chakraborti, S. Sreedharan, Y. Zhang, and S. Kambhampati, "Plan Explanations as Model Reconciliation: Moving Beyond Explanation as Soliloquy," in *IJCAI*, 2017.

[27] T. Chakraborti, Y. Zhang, D. Smith, and S. Kambhampati., "Planning with resource conflicts in human-robot cohabitation," in *AAMAS*, 2016.

[28] T. Chakraborti, G. Briggs, K. Talamadupula, Y. Zhang, M. Scheutz, D. Smith, and S. Kambhampati, "Planning for serendipity," in *IROS*, 2015, pp. 5300–5306.

[29] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," *IEEE Transactions on Systems Science and Cybernetics*, 1968.

[30] M. Ramırez and H. Geffner, "Probabilistic plan recognition using off-the-shelf classical planners," in *AAAI*, 2010.

[31] D. Bryce and S. Kambhampati, "A tutorial on planning graph based reachability heuristics," *AI Magazine*.

[32] L. Chrpa and R. Barták, "Reformulating planning problems by eliminating unpromising actions." 2009.

[33] Tathagata Chakraborti, Sarath Sreedharan and Subbarao Kambhampati, "Human-Aware Planning Revisited: A Tale of Three Models," in *IJCAI-ECAI 2018 Workshop on Explainable AI (XAI)*, 2018.

[34] T. Chakraborti, K. P. Fadnis, K. Talamadupula, M. Dholakia, B. Srivastava, J. O. Kephart, and R. K. Bellamy, "Visualizations for an explainable planning agent," *ICAPS UISP*, 2018.

[35] S. Sengupta, T. Chakraborti, and S. Kambhampati, "MA-RADAR – A Mixed-Reality Interface for Collaborative Decision Making," *ICAPS UISP*, 2018.

[36] T. Williams, D. Szafir, T. Chakraborti, and H. Ben Amor, "Virtual, augmented, and mixed reality for human-robot interaction," in *Companion of HRI Proceedings*. ACM, 2018, pp. 403–404.