Dynamic Path Visualization for Human-Robot Collaboration

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ABSTRACT

Augmented reality technology can enable robots to visualize their future actions giving users crucial information to avoid collisions and other conflicting actions. Although a robot's entire action plan could be visualized (such as the output of a navigational planner), how far into the future it is appropriate to display the robot's plan is unknown. We developed a dynamic path visualizer that projects the robot's motion intent at varying lengths depending on the complexity of the upcoming path. We tested our approach in a virtual game where participants were tasked to collect and deliver gems to a robot that moves randomly towards a grid of markers in a confined area. Preliminary results on a small sample size indicate no significant effect on task performance; however, open-ended responses reveal participants preference towards visuals that show longer path projections.

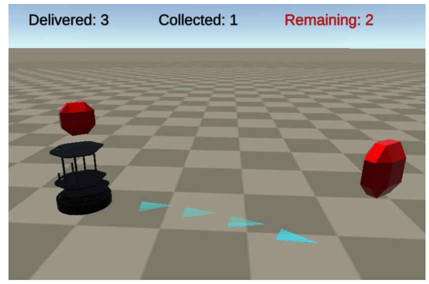

Figure 1: Screenshot of participant's first-person-view of a robot (Turtlebot2) projecting its path trajectory (Blue arrows) and game objects (red gems) that must be collected. Participant's progress and score are shown in text above.

CCS CONCEPTS

• **Human-centered computing** → **User interface toolkits**; **Visualization design and evaluation methods**; **User studies**.

KEYWORDS

Mixed-Reality, Augmented-Reality, Navigation

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1 INTRODUCTION

Robots that cannot express intentions due to the nature of their design or environmental restrictions can be unpredictable during normal operation resulting in undesired outcomes. These negative outcomes can be detrimental to human-robot trust when working together in a shared environment. Robots are capable of motion in a variety of ways (arm manipulators, UAVs, ground-mobile robots). Although humans can observe the robot's initial position, the final trajectory to reach their end state is mostly unknown unless time is taken to view the robot's trajectory with visual programs (e.g., Rviz). Having to switch from the physical environment to the display screen creates issues with aligning perspectives, which can be a mental burden.

To help address this problem, we can use the robot's action plan to inform humans of the robot's planned behavior. For example, a ground-mobile robot has a set of destination points and the determined path trajectory to reach each point. In this case, the robot's motion plan can be visualized in the context of the real-world using AR technology. Visualizing these movements can be helpful for short actions (i.e., robot moving to the next waypoint), however, it is not clear how far into the future the robot's plan should be projected to the user. It could be undesirable to show the entire planned path of the robot because it can be overwhelming especially if it contains several intersections or repeating laps. Our research addresses the following question: "how far into the future should a robot display its plan so that it is enough for humans to anticipate the robot's future location?"

If a robot's motion is simple, a person can make a reasonable guess of the robot's future location by observing its movement. However, it may be difficult to do so, if the robot's trajectory is complex or surprising. By comparing various projected path lengths, we can infer how much of the robot's future plan we need to show in order to improve task performance.

This work seeks to determine if visualizing a variable amount of information regarding a robot's intended path plan (based on path complexity) improves collaborative task performance. We created a virtual game where a participant must work with an autonomous robot to complete the task of collecting gems. During the task, the robot projects its path trajectory on the ground to show the participant its intended direction of motion (See Figure 1). Due to the small sample size, the quantitative evidence is limiting, but subjectively participants preferred projections of longer paths.

2 RELATED WORK

Communicating motion intent of a robot has been explored in several ways. Solutions include external attachments (e.g., LEDs [6, 8]

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and Light Projectors [17, 21]), motion patterns (e.g., flight patterns [16, 18], anticipatory motion [5, 7, 13], and deictic gestures [12, 22]), and verbal announcements [11]. Although these approaches are viable, they prevent the communication of long-term actions and potentially contribute to cognitive load. Our goal is to develop a method that conveys a robot's future navigation route in a quick and intuitive manner. We use augmented reality in simulation to evaluate our approach. By using simulation, we can render a path of any distance which may extend beyond the capabilities of a light projector.

Prior work in HRI has established that AR can be used to visualize robot data and future actions. Rosen et al. [15] developed a AR framework using a head-mount-display that visualizes an arm manipulator's intended motion trajectory to a goal state. Participants were asked whether the arm manipulator collides with an obstacle based on the visualized future trajectory of the arm. Quintero et al. [14] developed an AR-programming tool that enables users to control the actions of a robotic arm and preview the uploaded motion trajectory planner. Although both systems are successful in visualizing the arm-manipulator's future trajectory, the actions of the robot were short-term and predictable. In our study, we evaluated a robot's motion trajectory that varied in complexity using a ground-mobile robot.

Chandan et al. [2] developed an AR-interface that visualizes the path trajectories of multiple robots. However, the participant was engaged with completing a task that was not influenced by the robots' actions; therefore, participants did not gain any advantage with the visualized paths. Walker et al. [20] developed an AR framework that displayed a drone path with differing levels of explicit and implicit information regarding the drone's flight planner. In their collaborative task, participants were incentivized to leverage the flight path of the drone to perform their task efficiently. Although their framework can visualize the drone's future flight path, the extent of the visuals were purposely limited to a fixed amount of time or only to a few way-point destinations. In our study, we are evaluating how the extent of a robot's future path affects users' ability to perform collaborative tasks efficiently.

Muhammad et al. [10] created an AR-Robotic framework that visualizes a robot's sensor and cognitive data. Two of the visual options included *Global* and *Local* Path Trajectory where the robot's entire path or a partial path is rendered respectively. Here, we determined if there is an appropriate extent of our path visualization that provides users with enough information to determine the robot's intentions but does not become overwhelming due to visual clutter [19] or cognitive load [1].

3 METHODOLOGY

We designed a *2 x 4* within and between human-participant experiment. Participants play a game in a virtual environment with an autonomous robot, which is a component of our HAVEN simulator for virtual Augmented Reality HRI studies [3, 4]. Participants are tasked with collecting gems within a set time limit while the robot moves randomly within the same environment as the participant. The participant can only hold up to three gems at a time, and only by delivering the gems to the robot by contact (i.e., moving the player towards the robot's position) will the participant be able to collect more gems. The round is complete once all gems have been collected or if 2 minutes have elapsed. In this task, it would be beneficial for the participant to know ahead where the robot will be to deliver the gems they collected. We expect that users will take advantage of the path visualizations when the robot moves in a random and unpredictable manner. Because the robot is moving constantly, participates may resort to traveling in directions that position themselves in the path of the robot. Participants without path visuals may have a difficult time anticipating motion intent and will not have the opportunity to travel ahead of the robot.

For between-subjects, each participant is randomly assigned a projected path visual condition that determines the distance into the robot's future path trajectory that gets visualized. Conditions include: **(1) None**, where participants see no path), **(2) Continuous (Cont)**, where participants see the entire path, **(3) Fixed (Fix)**, where participants see a constant length path, and **(4) Dynamic (Dyn)**, where participants see a changing path length that is dependent on the path's curvature.

For within-subjects, we vary the complexity of the robot's path trajectory. The robot travels randomly in either a **(1) simple** or **(2) complex**; therefore, each participant plays a total of 2 rounds. With the following study design, we formed the following hypotheses:

H1: Users without visuals will perform worse than users with visuals.
H2: Users with **Dyn** visuals in complex path conditions will perform better than users with the other conditions.
H3: Users assigned the **Cont** condition will perform worse compared to users assigned with **Fix** or **Dyn** for complex paths.

3.1 Visualizing Path Trajectories

We can think of each visual path condition as having a "renderzone", Z, that has units of length which reveals the robot's path trajectory to the participant. Z acts like a sliding window that begins from the robot's position and moves with the speed of the robot. The length of this window depends of the selected condition. Our baseline conditions include the **None** and **Cont** that represent $Z = 0$ and $Z = \infty$ respectively. **Fix** is inspired by Walker et al. [20] where their *Arrow* visualization revealed 15 seconds of the robot's future path. After pilot testing with members of the lab, we selected the speed of the robot (10 units per second) and set Z to a constant value of 15 units that corresponds to 1.5 seconds. In the **Dyn** condition, Z changes according to the path's curvature or tortuosity. (i.e., a straight path yields a minimum distance projected while a curved path yields a larger distance projected). (Figure 2)

3.2 Z as a function of Path Complexity

We modeled the path trajectory of a robot as a curve, and the complexity of the curve is measured by a path's tortuosity. The more curvature a path contains, the harder we expect it would be for a person to predict the direction the robot will travel in the future. We calculate the path's Tortuosity, τ, using the formula:

$$\tau = C/L \tag{1}$$

where C is the total path length, and L is the distance between the path's end-points. Based on this equation, a straight line has $\tau = 1$, and a complete loop has $\tau = \infty$.

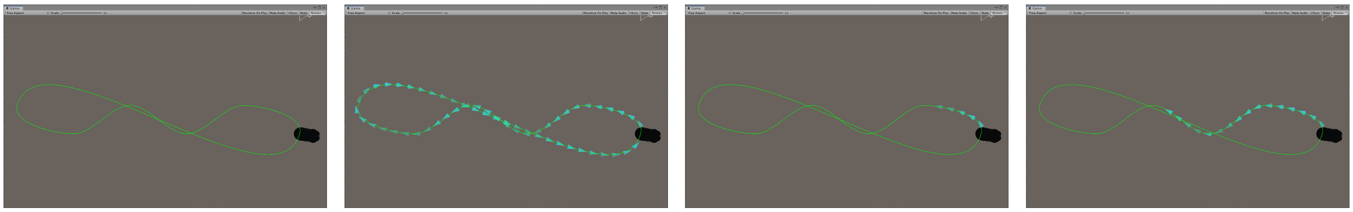

Figure 2: Path visual conditions from left to right: None, green line shows the path of the robot with no arrows, Continuous, blue arrows are shown along the entire path, Fixed, a specified amount of time is shown constantly, and Dynamic, a function that uses a natural logarithmic equation that takes the path's tortuosity as input to calculate the distance ahead of the robot's path to reveal.

The robot's path was divided into an equal number of segments to calculate local tortuosities. We use this approach because it is unreasonable to represent entire path with a single curve index considering how a robot's path can change and potentially produce locations where the path curvatures are dense. We used segments of length 200 units to ensure that the segments were not so small that the tortuosity was always close to 1. Our algorithm begins with the robot's path plan, P, which is an array of waypoint coordinates:

$$P = (x_i, y_i, \theta_i)_{i=1}^{N} \tag{2}$$

where (x, y) is the $X - Y$ coordinate, θ is the robot's orientation, and N is the size of the array. In this study, the robot's path plan lies entirely on the X-Z plane, but we note that it is possible to scale up a dimension to work in 3D-space. P is then used to generate a Beizer curve, and this curve is then segmented to map the local tortuosities along the robot's path. The value of Z changes as the robot makes its way along each new segment.

We used a natural logarithmic equation to calculate Z as a function of tortuostiy. Our logic is that no matter how dense a path is or how close a path is to reaching a closed loop resulting in enormous values of τ that may result in Z values may reach the entire length of the path, a participant may not need the entire path visualized. A qualitative evaluation revealed that the natural logarithm equation performed well even with large values of τ. We used the following equation for our **Dyn.** condition:

$$Z = C \times ln(\tau) + B \tag{3}$$

where C is a scalar constant units of length and B acts a y-intercept. The lowest possible value of τ being 1 (straight path) results in a minimum $Z = B$. We chose a value of 10 and 5 for C and B respectively after a pilot test on members of the laboratory.

3.3 Experimental Implementation

Our virtual environment was created in *Unity3D* and a demo version of our game is available on *simmer.io* [1]. The array, P, is used as input to generate a Beizer curve that the robot will follow within the environment. We leveraged the open-source *Path-Creator* [2] Github repository to generate the robot's path trajectories. To create the path trajectories for the robot, a grid of 25 waypoints lie within the virtual environment that is not seen by the participant. A complex path is generated by randomly ordering the sequence of waypoints that the robot will travel towards. The simple path is created using the same grid but with a reduced number of waypoints to create a relatively straighter path with fewer turns.

With the trajectories generated, a series of arrows are rendered along the curve at equal distances within the length of Z (see Figure 2: Far right). The **Dyn** condition was designed to avoid taking information away from a participant. In the case that the robot's path transitions from a curve to a straighter path, that is, Z decreases, then the extent of the visuals remain in place as the robot continues to travel along the path until the distance from the robot to the furthest visual equals the new value of Z.

3.4 Participants and Procedures

We have recruited a total of 36 participants (15 males, 17 females, and 4 who did not answer). The number of participants for each condition is currently unbalanced due to randomized assignment. We are continuing to recruit participants that experience simple and complex path conditions to compare for any learning effects. Participants in our preliminary data ranged in age from 19 to 64 (μ = 35.8,SD = 15.24). Participants also reported on a 5-point scale their familiarity with robots (μ = 2.4, SD = 1.3), video games (μ = 2.8, SD = 1.6), and augmented reality (μ = 1.8, SD = 0.8).

The entire study was held online and took approximately 20 minutes to complete the following steps: 1) The Participant on a web browser clicks on a Pre-survey link that will direct them to a survey to determine their eligibility; 2) The Participant then reads the purpose of the study and instructions on how to complete the study and electronically signs a consent form; 3) The participant then completes the game demo, where further instructions are given such as the task objective, how to move within the virtual environment, and how to collect and deliver virtual objects. Participants can take this opportunity to be familiar with moving their virtual character using the mouse and keyboard controls; and 4) After the participant completes the 2 rounds of the study, they then answer a post-survey regarding their interactions with the robot.

3.5 Measures & Analysis

We use a combination of objective and subjective measurements to evaluate our four visualization options. Objective measures include the **Time of completion** and the **number of gems collected** each round and the **orientation** of the robot and player for every delivery. Users that performed efficiently completed their task in shorter times and collected most of the gems.

[1] https://simmer.io/@DreVinciGames/haven-test/
[2] https://github.com/SebLague/Path-Creator

The location and rotation of the robot relative to the player are recorded once the user makes contact with the robot to deliver their collected gems. For simplicity, we are interested in whether the player interacted with the anterior or posterior side of the robot. The robot is divided into 2 sections that correspond to the sides of the robot (i.e., anterior and posterior) by placing point markers around the robot. The direction of approach the participant intersects with the robot triggers one of the markers. For each collision detection, a tally for the selected marker is recorded for every delivery the participant makes. Markers that circle around the front of the robot(0-180 degrees) count towards the anterior while the remaining side count towards the posterior. Participants will anticipate the robot's trajectory more with visuals by positioning themselves on the anterior side of the robot before delivery.

Subjective measures were gathered to gauge participants' perceptions and preferences using a series of 7-point Likert-style questionnaire. Scales rated "the robot was helpful in completing your task", "the robot communicated its motion intentions clearly", "how safe you expect this robot to be in a public environment?". Open-ended responses were gathered for qualitative feedback. Responses included: "Describe your experience completing the task", "Describe any strategy you used to complete the task", "Describe your experience seeing the robot's path trajectory if applicable". We then gathered the participants perceived cognitive workload using the NASA Task Load Index (NASA-TLX) questionnaire [9].

4 PRELIMINARY RESULTS

Our initial approach of randomly assigning conditions created ordering effects as participants are often first shown the simple condition. To address this issue, we implemented block randomization to counterbalance the conditions. Figure 3 reveals the average time completion for each condition per round. We are currently gathering more participants due to our low sample sizes. However, given the data for the complex paths for both the **None** and **Dyn** conditions, a T-test has not found a significant effect ($p = 0.48$). When comparing within-groups (Simple to Complex), both have shown significant effect, ($p = 0.025$), ($p = 0.027$) respectively. In the simple path condition, 8 participants received the **None** condition, 2 participant for the **Cont.** condition, 3 participants for the **Fix.** condition, and 10 participants for the **Dyn.** condition. In the complex path condition, we have 2 participants in the **None** condition, 4 participants for the **Cont.** condition, 2 participant for the **Fix** condition, and 5 participants for the **Dyn** condition. The time of completion for each round is averaged as well as the participants perceived rating for Clarity, Helpfulness, and Safety.

5 DISCUSSION AND FUTURE WORK

Despite our small sample size, participants' open-ended responses have revealed surprising themes regarding their strategy in completing their objective. Participants assigned **None** collected gems in random order and mostly chased the robot. Some reported anticipating the robot's path trajectory because they soon picked up on the repetitive path pattern. **P11[None]** *"It was sometimes frustrating to catch the robot at first before I better figured out its movement patterns, but once I figured it out it was better..."*

Participants with visuals reported that they could wait and let the robot come to them once they positioned themselves in the projected path. **P12 [Cont]** *"The robot always showed its trajectory for me. So it was easy to get in front of the robot. "* **P14 [Dyn]**: *"The path trajectory was a great way for me to know where to go for delivery. I would just stand on the path and wait (not too long, because it's a nice short length) for the robot to run through me."* Participants taking time positioning themselves in the robot's path instead of continuously moving towards the robot contributes their overall time in each round which may affect **H1**.

Regarding the length of the projected robot's path, few participants expressed how they preferred having more visuals: **P19 [Fix]** *"...it'd be nicer if you have more of the robot's path trajectory."*

Based on the preliminary responses, we expect participants with the **Dyn** and **Cont** visuals performing and rating higher than the other conditions considering they can provide an extended amount of information (**H3**). We originally hypothesized that projecting the entire path (**Cont**) especially for complex paths would be overwhelming for the participant resulting in poor performance **H4**. While this still maybe the case, it is worth exploring alternate ways to generate varying path complexities and conduct a manipulation check to determine if participants do perceive a path as predictable or not. It can be argued that there is a slight advantage to the complex path as it influences where robot spends most of its time during the round. If the robot moves within in a concentrated location, then the distance for the participant to travel is shorter. **P21[Dyn]** *"The first time was harder because the robot always seemed far away even when I knew its path, but the second time was easier since its path trajectory always seemed to be going towards me...*

For future work, we would like to investigate the effect of varying the velocity of the robot on the extent of the robot's path. Our robot's speed was constant which allowed us to focus on the complexity of the robot's path trajectory as well as simplify the calculation of Z. Our work can provide insights to how we design robots that are intended to operate "in the wild" and provided humans with an adequate amount of information to operate safely in a shared environment.

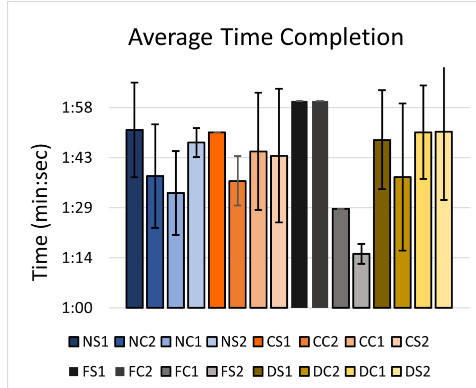

Figure 3: Average Time completion for each condition. First letter indicates condition, second letter indicates path condition, and the number indicates round)

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