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Through the Clutter: Exploring the Impact of Complex Environments on the Legibility of Robot Motion

Melanie Schmidt-Wolf[1], Tyler J Becker[2], Denielle Oliva[3], Monica Nicolescu[4], and David Feil-Seifer[5]

***Abstract*— The environments in which the collaboration of a robot would be the most helpful to a person are frequently uncontrolled and *cluttered* with many objects present. Legible robot arm motion is crucial in tasks like these in order to avoid possible collisions, improve the workflow and help ensure the safety of the person. Prior work in this area, however, focuses on solutions that are tested only in *uncluttered* environments and there are not many results taken from *cluttered* environments. In this research we present a *measure for clutteredness* based on an entropic measure of the environment, and a *novel motion planner* based on potential fields. Both our measure and the planner were tested in a *cluttered* environment meant to represent a more typical tool-sorting task for which the person would collaborate with a robot. The in-person validation study with Baxter robots shows a significant improvement in legibility of our proposed legible motion planner compared to the current state-of-the-art legible motion planner in *cluttered* environments. Further, the results show a significant difference in the performance of the planners in *cluttered* and *uncluttered* environments, and the need to further explore legible motion in *cluttered* environments. We argue that the inconsistency of our results in *cluttered* environments with those obtained from *uncluttered* environments points out several important issues with the current research performed in the area of legible motion planners.**

I. Introduction

In human-robot collaboration tasks it is inefficient, frustrating, and a safety hazard when the intended goal of the robot is unclear. When people work together to complete a task they communicate both explicitly (e.g., verbally) and implicitly (e.g., through arm motions) in order to show their intention. This way they are able to avoid collisions and overall increase the efficiency with which they can complete the task. For robot collaborators the task is harder, as expectations from the human for the robot are higher overall than when working with another person. Furthermore, the patience when this collaboration fails is much smaller.

This problem becomes even more difficult in *cluttered* environments because the effectiveness of both explicit and implicit communication decreases due to the increased number of objects in the scene and as well due to their close proximity to each other. Furthermore, as the sensitivity of the environment increases so does the importance of preventing collisions. In this paper, we investigate legible motion in *cluttered* environments which focuses on the ability of the robot to express its intent implicitly through the trajectory of its arm while completing a task.

(a) One of the Baxter robots with an *uncluttered* environment setup (b) Another Baxter robot with a *cluttered* environment setup

Fig. 1: Baxter humanoid robots with the two environment setups used in the validation study.

Previous solutions developed for legible motion have modeled it as an optimization problem for which the constraints are defined using a variety of methods. Previously proposed constraints include:

- relative position to the goal;
- the orientation of the end effector;
- the velocity of the end effector;
- the overall distance of the trajectory;
- dissimilarity to other trajectories; and
- linearity of the path.

The results of these different methods were shown experimentally through user studies, however, the user studies were designed using simple *uncluttered* environments.

While useful for initial studies, *uncluttered* environments are not the norm for tasks where robot collaboration would be useful (e.g., cleaning tasks or sorting tasks). Therefore, in this work we test the previous state-of-the-art as well as a logical extension of that method in both an *uncluttered* and a *cluttered* environment (shown in Fig. 1) in order to determine both what effect a *cluttered* environment has on the accuracy with which the intention can be determined and the effectiveness of the previous optimization criteria.

[1]Melanie Schmidt-Wolf, [2]Tyler J Becker, [3]Denielle Oliva, [4]Monica Nicolescu, and [5]David Feil-Seifer are with the Department of Computer Science and Engineering, University of Nevada, Reno, 1664 N. Virginia Street, Reno, NV 89557-0171, USA *mschmidtwolf@unr.edu*, *tbecker@unr.edu*, *denielleo@unr.edu*, *monica@cse.unr.edu* and *dave@cse.unr.edu*

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The major contributions of this paper are as follows:

- A mathematical definition of the *clutteredness* of a table environment based on the concept of entropy;
- A novel algorithm for generating legible motion trajectories based on the concept of entropy-scaled potential fields;
- Demonstration of the impact of an environment's *clutteredness* on the planner's performance; and
- An in-person user study using Baxter robots to evaluate the effectiveness of two different legible motion planners in both *cluttered* and *uncluttered* environments.

II. Related Work

A. Legible robot arm motion

Legible robot motion implicitly expresses the intent of the robot to increase the understanding of a human collaborator. Further, legible robot motion is defined as motion that allows the human collaborator to infer the correct target object quickly and confidently [1]. Prior work in this area has focused on developing motion planners which express the information in a way that people can understand more easily. Dragan et al. [1] developed mathematical models to define and distinguish predictability and legibility. This was evaluated in an *uncluttered* environment with two objects using recorded videos. Ngo and Steinfeld [2] studied potential-vector fields with two objects and validated the results by calculating the area under the legibility curve and total path length, in comparison with Dragan et al. [1]. Bied and Chetouani proposed a solution using reinforcement learning [3] to maximize their proposed metric for legibility. This was evaluated in an abstracted graphical environment and was not tested through a user study. As such, it was evaluated with a single object in an *uncluttered* environment with a variable number of observers. Faria et al. [4] proposed a solution for multiple people observing a motion which involved optimizing for the best value for them all rather than just a single person. This was evaluated in an *uncluttered* environment using videos produced in simulation to show participants of a user study. Wallkötter et al. [5] utilized supervised learning to generate legible motion by training on data that was evaluated and labeled through legibility measures that had been tested in prior works. The testing environment they used included seven unevenly spaced objects, and their results were validated through scoring accuracy and not through a user study. Most recently Bronars et al. [6] used conditional generative models guided by legibility measures from previous work to generate legible motion. This system was evaluated through comparison to other planners by scoring their legibility with a measure, and they used an *uncluttered* environment with two evenly spaced objects.

A survey of ten legibility frameworks was provided by Wallkötter et al. [7] and they found that the legibility framework from Bodden et al. [8] performed the best. However, the planners in this survey were tested in a simulated *uncluttered* environment with three objects present.

In this research, we validate the chosen legible motion planners on real robots in a *cluttered* and *uncluttered* environment. The potential inconsistencies between *cluttered* and *uncluttered* environments may present significant challenges for existing approaches when employed in real-world environments. To address these challenges, we evaluate the use of potential fields as a possible solution for legible motion in *cluttered* environments. We also evaluate this approach through an in-person user study with the motion planner on a real robot, and we investigate if clutter has an impact on the legibility of the motion planners.

B. Cluttered Environment Measures

As illustrated in Fig. 1, the experimental validation will explore both an *uncluttered* and a *cluttered* environment. We expect that it might be more difficult for the robot arm to move legibly in a *cluttered* environment. In this work, we want to test and evaluate a robot's motion in a *cluttered* environment. To achieve this, we need a measure for a *cluttered* environment to consider the amount of *clutteredness* in the shared workspace.

Clutteredness is typically measured as a ratio of occupied and total space. This includes the number of obstacles affecting the robot, defined as the ratio of sensed obstacles to a preset *clutter* value [9], as a measure proportional to voxel numbers from voxel occupancy grids [10], or from a computer vision perspective as the sum of spectral residual values of the pixels and the total pixels in the candidate regions [11]. *Clutter* can be defined as the distance between objects or if objects are in contact with each other by filtering through a point cloud of pixels [12]. Further, entropy can be associated with disorder [13]. In this paper, we establish a *cluttered* environment measure from the Kullback-Leibler Divergence [14] which is based on entropy.

Other works [15], [16], and [17] propose methods for manipulating objects in *cluttered* environments with the goal of finding valid paths, but not with the goal of legible motion in the case of human-robot interaction in a *cluttered* space. The work in this paper investigates legible robot motion with the assumption of collaboration in a shared space.

C. Potential Fields

Artificial potential fields was proposed by Khatib [18] as a real-time obstacle avoidance approach. The artificial potential field approach bases the motions of the robot on how it would move if it were being affected continuously by artificial forces assigned to obstacles in the environment. The field consists of an attractive force to move towards the target and a repulsive force to avoid obstacles. Other work employed a potential field method to design safe path planning in a collaborative task [19]. This method considered a hand of a human collaborator as an obstacle that affected the paths that could be taken in a dynamic assembly task.

Although potential field algorithms are commonly used in robot path planning for obstacle avoidance, they have not been used to create legible motion. In this paper, we apply potential fields with forces scaled by our *clutteredness* measure to make the robot arm motion more legible.

III. Approach

In this section, we describe our novel definition of the *clutteredness* of objects in an environment, and a novel architecture for legible motion based on potential fields.

A. Clutteredness Measure

In order to measure the *clutteredness* of the environment, we use the concept of entropy from information theory, which gives an estimate of the surprise of receiving some given results produced by some distribution [20]. We connect this to *clutteredness* by comparing the distribution of objects in the environment to an imagined uniform distribution of the same objects. For this measure, objects that are uniformly distributed are considered not *cluttered*, and therefore we estimate the distribution of object positions as a multivariate Gaussian and compare it to the uniform distribution using the *Kullback-Leibler Divergence* [21] as shown in Eq. 3.

$$h(p) = \mathbf{E}[-\log p(X)] = -\int_X p(x) \log p(x) \mathbf{d}\boldsymbol{x} \tag{1}$$

$$h(p, q) = \mathbf{E}_p[-\log q(X)] = -\int_X p(x) \log q(x) \mathbf{d}\boldsymbol{x} \tag{2}$$

$$D(p \| q) = -h(p) + h(p, q) \tag{3}$$

In the equation, p is the estimated Gaussian distribution, q is the Uniform Distribution, X is a random variable, x is an instance of X, $h(p)$ is the entropy, and $h(p, q)$ is the cross-entropy of the two distributions. This measure of divergence is unbounded and therefore not suitable as a scaling factor, so we use the nonlinear normalized transformation shown in Eq. 4 to get our measure for clutter ξ.

$$\xi = e^{-D(p \| q)} \tag{4}$$

This transformation guarantees that the value of ξ is always positive and normalized.

B. Legible Potential Fields

The potential fields algorithm for robot navigation assigns a virtual repulsive force to obstacles in the environment and a virtual attractive force to the target (see [18] for a general overview). The robot is pulled toward the target and pushed away from obstacles, creating a collision-free path.

For this paper, we applied this theory to trajectory planning in order to achieve legible motion in *cluttered* environments. Our virtual attractive force is assigned to the target object and all other objects in the environment are assigned a virtual repulsive force, which is scaled based on the measured ξ value of the environment and a measure of how close the object is to a straight line trajectory. We then apply these forces to the position of the end effector until it reaches the target object, and we obtain a collision-free trajectory that leads to the target. A smoother is also applied to the trajectory, which both ensure that the path gives the obstacles a wider margin and that the trajectory only decreases in height. An example output of the potential fields algorithm is shown in Fig. 2.

Our assumption is that this will produce legible motion in *cluttered* environments because this follows the optimization

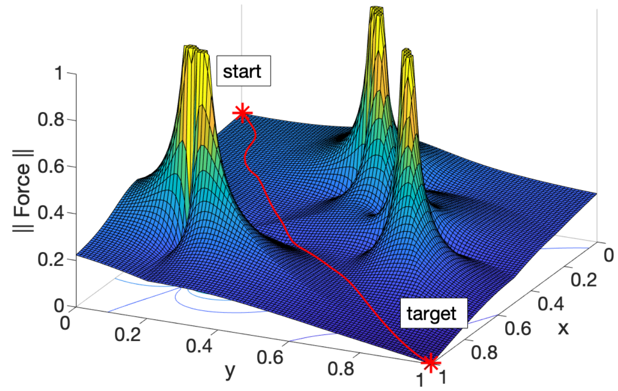


Fig. 2: Visual explanation of the path generated by the potential field, displayed with three obstacles.

parameters described by Bodden et al. in [8]. They describe three parameters that they optimize for motion legibility: *Point Position*, *Pointing*, and *Velocity*. The results shown by Bodden et al. [8] are not promising with respect to *Pointing*, and therefore we have omitted this consideration from our planner, as well as the implementation of their planner in the study whose results are shown in Section V. However, we will describe below how calculating the trajectory with potential fields naturally follows both the *Point Position* and *Velocity* parameters in *cluttered* environments.

Point Position is described as a heuristic that predicts the goal of a trajectory based on which object is closest to the position of the end effector. By optimizing this value for the target object, the motion planner generates trajectories, which stay higher up until the end effector is over the goal and then immediately drops down to the object as shown in Fig. 3. Potential fields produce similar trajectories because of the force in the z-direction, which forces the trajectory to stay far above objects. The trajectories generated from potential fields are lower than the trajectories of the state-of-the-art planner; we expect this will help to convey closeness to the target in the *cluttered* environment.

Velocity is described as a heuristic, which rewards the end effector for moving faster when farther away from the target object. This is under the assumption that the person will try to extrapolate the target using this information and the distance from other objects. Potential fields naturally do this, as the attractive force is greater the farther the end effector is from the target object, resulting in a higher speed. The difference of the proposed planner to the state-of-the-art is that the generated trajectory will slow down in order to move around objects that are in the way. We think this will give more information to the person collaborating with the robot in the *cluttered* environment.

The results of testing both our planner and the state-of-the-art planner in our in-person study are shown in Section V.

C. Algorithm

In Alg. 1, we show the potential fields method used for the legible motion planner. In this representation, ϵ is the minimum distance to the target, ∇U_{att} is the total attractive force, ∇U_{rep} is the total repulsive force, k_{update} is the gain applied to the total force, and ξ is defined in Eq. 4. For this research, we additionally apply a post-processing algorithm to the trajectory in order to smooth it and ensure that the trajectory is always decreasing in height. This results in more direct motions towards the target.

Algorithm 1 Returns a legible trajectory from the starting position of the end effector to the position of the target object. $\vec{x}_{ee}$ is the starting position of the end effector and j is the index of the target object.

```
procedure genLegibleTraj(x_ee, j)
    x_plan ← x_ee,  traj ← [ ]
    while ||x_plan − x_j|| < ε do
        traj ← traj ∪ [x_plan]
        ∇U_total(j) ← ∇U_att(j) + ξ∇U_rep(j)
        x_plan ← x_plan − k_update ∇U_total(j)
    end while
    return traj
```

procedure $genLegibleTraj(\vec{x}_{ee}, j)$
  $\vec{x}_{plan} \leftarrow \vec{x}_{ee},\ traj \leftarrow [\ ]$
  while $\|\vec{x}_{plan} - \vec{x}_j\| < \epsilon$ **do**
    $traj \leftarrow traj \cup [\vec{x}_{plan}]$
    $\nabla U_{total}(j) \leftarrow \nabla U_{att}(j) + \xi \nabla U_{rep}(j)$
    $\vec{x}_{plan} \leftarrow \vec{x}_{plan} - k_{update} \nabla U_{total}(j)$
  end while
  return $traj$

Fig. 2 illustrates a potential field for three obstacles and a target object. The generated path from the end effector's start position to the target avoids moving towards the obstacles, thereby improving legibility. Fig. 3 visualizes a *cluttered* environment with three comparisons between the state-of-the-art and our proposed approach, emphasizing improved legibility by avoiding other objects in the shared workspace.

IV. Experimental Validation

We conducted a validation study with two Baxter robots (see Fig. 1) to verify if the proposed legible motion planner generates more legible robotic grasping motions than established methods by using potential fields and entropy. Additionally, we aimed to evaluate if there are potential inconsistencies between *cluttered* and *uncluttered* environments that may pose challenges for existing approaches when applied in real-world environments. 40 participants were recruited via flyers and social media to participate in the IRB-approved (IRBNet ID: 2090377-2) study. The user study had a duration of about 30 minutes.

A. Hypotheses

In this study, we investigate the following hypotheses:

- **H1:** Clutter has a negative impact on the legibility of the motion.

We will assess the validity of H1 by comparing participant's estimated target accuracy in the *uncluttered* and the *cluttered* experiment setup by testing significance to determine differences between both experiment setups.

- **H2:** The proposed legible motion planner will result in more legible motion for:
    1) *uncluttered* environments; and
    2) *cluttered* environments

  compared to the state-of-the-art legible motion planner from Bodden et al. [8].

To validate H2, we will compare the participant's responses for both legible motion planners for the *uncluttered* environment (hypothesis 2.1) and the *cluttered* environment (hypothesis 2.2). The comparison will be conducted using statistical tests for significance to identify any significant differences between both legible motion planners.

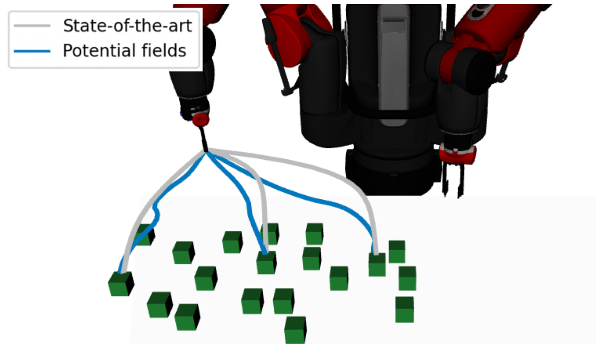


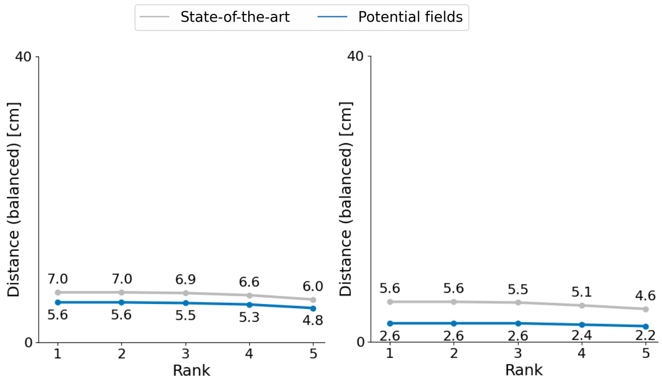
Fig. 3: Comparisons of the trajectories of the state-of-the-art legible motion planner (gray) and our proposed legible motion planner based on potential fields (blue). Our entropy-scaled potential field legible motion planner avoids other objects (green), which leads to more legible motion.

B. Study Design

In this validation study, participants were asked to observe the robot as it picks up an object among many in a *cluttered* environment. The trajectories were split into sections and after each section the participants were asked which object they think the robot is reaching for by ranking their choices from one to five, with rank 1 being their first choice. The participants answered questions about the executed motion and repeated this for different objects. Since every participant evaluates both the proposed legible motion planner and the state-of-the-art legible motion planner from Bodden et al. [8], this study employs a within-subjects design. The survey concluded with demographic questions. For the study, we used two experiment setups. The first experiment setup places the objects as in the state-of-the-art paper with five objects next to each other, see Fig. 1a. The second experiment setup consists of a *cluttered* environment with 20 objects, see Fig. 1b. The first experiment setup has a *clutteredness* measure of ξ=1.0 and the second experiment setup has a *clutteredness* measure ξ=0.06. In the validation study, the participants do not know which ten of the 20 objects the robot will approach. The order of the target objects and the motion planner were randomized.

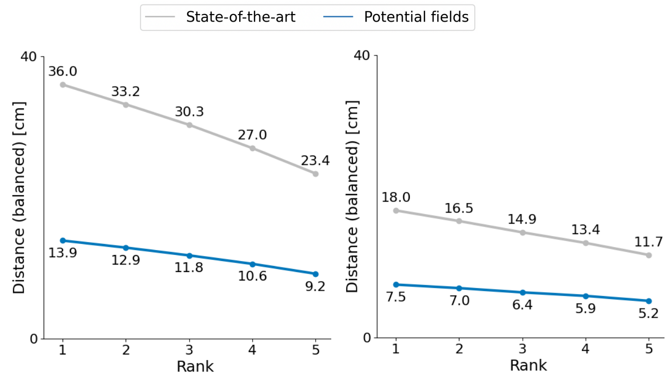
V. Results

Fig. 4 shows the user study results for the *uncluttered* environment. In Fig. 5, the comparison results of our entropy-scaled potential field planner and the state-of-the-art legible motion planner are visualized for the *cluttered* environment. It is challenging to compare motion planners for objects in different parts of the environment because each object has a different distance and arrangement to other objects, and therefore the trajectories have a different legibility dependent on clutter. We compare the average distance to the correct object for the planner balanced by the average distance to other objects in the environment. The rank values in Fig. 4 and 5 are obtained by summing up the distances of the guessed



(a) *Uncluttered* setup: Section 1 (b) *Uncluttered* setup: Section 2

Fig. 4: In an *uncluttered* environment our entropy-scaled potential field legible motion planner and the state-of-the-art legible motion planner perform similarly well (p-values > 0.05). In both sections of the trajectory, participants seem quite certain which object will be picked, especially when comparing the values with the values in Fig. 5 (lower distances to the target object are better).



(a) *Cluttered* setup: Section 1 (b) *Cluttered* setup: Section 2

Fig. 5: In a *cluttered* environment our entropy-scaled potential field planner performed significantly better compared to the state-of-the-art planner with a (a) p-value < 0.001 and a (b) p-value < 0.05 (Wilcoxon signed-rank test for the first rank). Especially in the first trajectory section, participants seemed uncertain regarding which object the robot would grasp (lower distances to the target object are better).

object to the correct object until the participant guessed the correct object. Based on the Shapiro-Wilk test results ($p < 0.05$), normality cannot be assumed. Consequently, non-parametric tests were utilized to determine significance.

A. Impact of Clutter on Legibility

To address H1, we compared the results of the *uncluttered* and the *cluttered* experiment setup for both sections for the first rank. The statistical analysis results indicate a significant difference between the *uncluttered* and the *cluttered* experiment setups, with p-values < 0.001. This significant difference was observed in both legible motion planners.

Comparing Fig. 4a and 5a, as well as Fig. 4b and 5b shows that participants demonstrated higher accuracy in selecting the correct object in the *uncluttered* setup than in the *cluttered* setup. The average distance of the participants' guesses to the correct object is consistently larger in the *cluttered* than in the *uncluttered* setup.

B. Legible Motion Planner Comparison

To address H2, we compared the results of our proposed and the state-of-the-art legible motion planner.

1) Uncluttered Environment: In the *uncluttered* environment, the legible motion planners perform similarly well with p-values > 0.05 for both trajectory sections and therefore no significant difference. Fig. 4 visualizes these results, showing that participants were generally confident about which object would be picked. The lower average distance values in Fig. 4b compared to Fig. 4a suggest participants became more certain as the robot arm neared the target object.

2) Cluttered Environment: In the *cluttered* environment setup, our entropy-scaled potential field planner performs significantly better than the current state-of-the-art legible motion planner. This was tested using the non-parametric Wilcoxon signed-rank test, as normality could not be assumed (see beginning of Section V). The significance test resulted in a p-value < 0.001 for the first section and a p-value < 0.05 for the second section of the trajectory.

Participants answered on average with a closer distance towards the correct object with our entropy-scaled potential field planner than with the state-of-the-art planner. I.e., participants are more confident in choosing the correct object, demonstrating an improvement of our entropy-scaled potential field planner compared to the state-of-the-art. Further, in the first section of the trajectory, participants were still uncertain about the robot's target, but in the second section, they became more accurate in guessing the correct object (lower distance of rank 1 in Fig. 5b than in Fig. 5a).

C. Open-Ended Questions

In terms of what would make legible motion planners better for *cluttered* environments, we left the question open to participants of the study and we will include interesting responses as well as our thoughts below.

Overwhelmingly, participants recommended smoother motions in contrast to the potential fields planner and found that any sharp turns to be confusing. Many participants who felt this way also recommended straight lines. While this was found to be less accurate by Bodden et al. [8], it was not tested in *cluttered* environments so the results of a straight line planner could be worth testing again. Many participants also found the sudden stops of the motion to be confusing so it is worth considering only testing full motions for experimental validation resetting each time a guess is taken. This suggestion only pertains to the overall collection of results, however, and is not necessarily helpful for the design of the motion planner. Some participants recommended more direct motions toward the object rather than the "hovering" behavior of the state-of-the-art planner. Overall, we did not receive consistent answers to the open-ended questions, suggesting that individual preferences influence expectations regarding the robot's behavior.

VI. Discussion

A. The Effect of Clutter on Legibility

The results of the experimental validation study show a significant improvement in legibility of our proposed legible motion planner compared to the current state-of-the-art legible motion planner in *cluttered* environments. The results also emphasize the need to further explore legible motion in *cluttered* environments [22]. We showed that potential fields can be used to induce legibility of robot motion by avoiding to move towards objects other than the target. This is most likely due to the improvements that we made to the optimization criteria presented by Bodden et al. [8] for application in *cluttered* environments.

Based on the experimental results, H1 is *supported*, as shown by the significant differences between the *uncluttered* and the *cluttered* experiment setups, compare Fig. 4 and 5.

As expected, H2.1 is *not supported* by the experiment results, as there is no significant difference between the two planners, see Fig. 4. In the *uncluttered* environment, both planners generated similar trajectories, with the entropy-scaled potential fields planner utilizing a different strategy to optimize the same parameters as the state-of-the-art planner.

H2.2 is *supported*, as shown in the results reported in Fig. 5. This is due to the fact that there are both more objects and the objects are *cluttered*, which can mean they are bunched together and lowers the legibility of motions towards specific objects. This lowers the potential benefits that a person could receive from collaborating with a robot using either of these legible motion planners. If that person cannot guess reliably what the robot is reaching for in the environment presented in this paper, then in more *cluttered* environments or more sensitive environments they will not feel as comfortable collaborating with and trusting the robot.

Our proposed entropy-scaled potential field legible motion planner performed significantly better in the *cluttered* environment than the current state-of-the-art legible motion planner. However, to further improve the performance of legible motion planners in *cluttered* environments, it is necessary to conduct more research as indicated by the open-ended participant responses. Previous legible motion solutions, though less effective in *uncluttered* environments, may still hold potential for *cluttered* scenarios. Since no correlation between performance in *uncluttered* and *cluttered* environments has been found, it remains unclear whether these solutions should continue to be discarded as suboptimal.

B. Recommendations for Legible Motion Planner Research

Legible motion is currently focused on overly-controlled environments with a limited number of regularly spaced objects. However, human-robot collaboration is primarily uncontrolled with a variably large number of objects. The goal of research performed in this area is to build systems for implicit communication on the part of the robot which will enable the human to guess its intent in these scenarios. An underlying assumption in prior work is that by studying a simpler version of this problem, *uncluttered* environments, solutions can be created, which will then extend to harder versions of the same problem, *cluttered* environments. The results of this study conclusively show that this assumption is not true since the proximity of objects and the number of object choices introduce many added complexities.

We propose the following suggestions to improve data collection and evaluation in *cluttered* environments. First, performance measures for accuracy and legibility should be developed based on how well people convey their intentions. Our research demonstrates that the state-of-the-art planner does not perform well in *cluttered* environments, so comparing against it can only give us relative information about how well our planner performed. Utilizing human-human legibility studies could provide valuable accuracy metrics for evaluating robot-human interactions. Second, it is important to differentiate legible motion strategies for trained and untrained collaborators. The effectiveness of different strategies may vary based on the collaborator's level of familiarity with the robot. For instance, an intuitive metric for a trained collaborator would be consistency of approach, whereas an untrained collaborator may not find mere consistency as effective or beneficial. Finally, differences between in-person and simulated robot evaluation may significantly affect legibility metrics. Factors like the robot's physical presence, participant perception, and field of view are limited in simulations, which could impact study outcomes.

Overall, the results of this validation study demonstrate that clutter significantly impacts the planner's performance. It emphasizes the importance of clutter in testing planners since a planner that performs well in an *uncluttered* environment is not necessarily valid in a *cluttered* environment.

VII. Conclusion

We investigated legible robot motion in *cluttered* environments. We presented a novel definition of the *clutteredness* of objects in a table-top environment and a definition of the legibility with which an object can be grasped.

Previous legible robot motion planners were tested in *uncluttered* environments. Since *cluttered* environments frequent human-robot collaboration, we tested the previous state-of-the-art and a logical extension of that method based on entropy-scaled potential fields for both *uncluttered* and *cluttered* environments. The validation study results show a significant improvement in legibility over the state-of-the-art legible motion planner in *cluttered* environments. However, the results also show the need to explore legible motion in *cluttered* environments further to develop an adequate solution to generalizable legible motion planning.

The results show that testing legible motion planners in *uncluttered* environments may not necessarily produce outcomes that are applicable to *cluttered* environments. As such, it is imperative to conduct research that takes into account the impact of clutter on the performance of these motion planners. Our recommended modifications to the method of researching legible motion planners are expected to result in more generalizable planners that are applicable in real-world environments.

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