A Virtual Manipulation Task to Probe Human Interactions with Diverse Physical Objects

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Abstract

Humans are able to successfully interact with objects with vastly different physical characteristics. For example, hard objects, such as boxes, and soft objects, such as cloth or rope, behave in entirely different ways when manipulated. We designed a controlled yet ecological behavioral task to probe how human subjects interact with objects with diverse physical characteristics. Subjects are shown, on a computer screen, an 'arena' including an object, a simple manipulator (a rectangular pusher) and a goal indicated by a location within the arena. Using the keyboard, they can rotate and translate the pusher, and their task is to use it to push the object into the goal. On each trial, the object to be moved belongs to one of three categories: box, rope, or cloth. This task allows systematically comparing human behavior across object categories in a simplified scenario, providing an ideal testing ground for computational models of object manipulation and intuitive physics.

Keywords: manipulation; intuitive physics; internal models; videogames

Introduction

In our daily life, we routinely manipulate objects with extremely diverse characteristics. These range from rigid objects, that maintain the same shape when manipulated, to soft objects which can be deformed. Deformable object manipulation is a notoriously difficult task, as it involves the exploration of an extremely vast space of configurations. While this task has been extensively explored in robotics (Yin, Varava, & Kragic, 2021), human behavior in manipulating deformable objects, to the best of our knowledge, has only been investigated in a few studies (Mazzeo et al., 2024). Here, we propose a simplified virtual environment to systematically evaluate differences in manipulation behavior across diverse types of objects, including one rigid object (a box) and two deformable objects (a piece of cloth and a rope). We chose object categories that have been broadly used as a testing ground for flexible manipulation in robotics (Zhang, Li, Hauser, & Li, 2024). Subjects see a simple scene on a computer screen comprising a square 'arena' including an object, a simple effector (a rectangular pusher), and a goal location within the arena. Using the keyboard, they have to push the object into the goal location by translating and rotating the pusher. This task can be easily extended to include different objects, effectors or goal configurations. As it was programmed using the popular game engine Unity (Unity Technologies), it can also be deployed across diverse platforms, including virtual reality or online studies, and used to train agents using frameworks such as Unity ML-Agents (Nandy, Biswas, Nandy, & Biswas, 2018). We present some examples of the kind of data that can be extracted from this task.

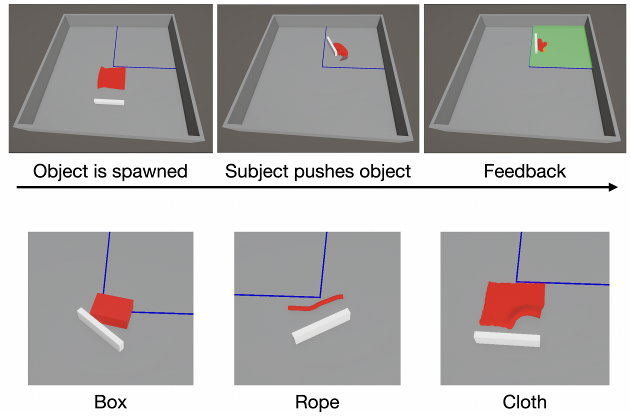

Figure 1: Illustration of the trial sequence, and of the three objects used in the task.

Method

Task Environment

The task environment was programmed using the Unity game engine (Unity Technologies), and the Unity Experiment Framework (UXF) (Brookes, Warburton, Alghadier, Mon-Williams, & Mushtaq, 2020) for controlling trial variables, tracking object locations and the experimental logic more in general. The deformable objects were simulated using the Obi particle-based simulation assets (Virtual Method).

Experimental Design

We vary the target object type (box, cloth, and rope) and the goal location (left and right), leading to 6 unique conditions. At the beginning of a trial (Fig. 1), the goal location becomes visible and the target object is 'spawned' by dropping it from a small height in front of the pusher, at the center of the arena. The subject has to use the down/up arrow keys to move the pusher back and forth, and the right and left keys to rotate it clockwise and counterclockwise, respectively. The instructions are to push the object until it is entirely inside of the goal area, and then press the space bar to conclude the trial. The goal area then changes color for 500 ms: green if the object is fully inside, red otherwise, providing feedback. Then the following trial starts.

Results

In Fig. 2, we show examples of the object and pusher trajectories in the different conditions, for a single subject undergoing 8 trials per unique condition (48 trials in total). These results are meant purely as an illustration of the rich information that can be obtained from this task, rather than as a full dataset. However, we can already observe several regularities, such as the high variability in the cloth trajectories, and the higher curvature of the rope trajectories compared to the box.

Conclusion

We have presented a task designed to probe, in a simplified environment, the human ability to interact with diverse physi-

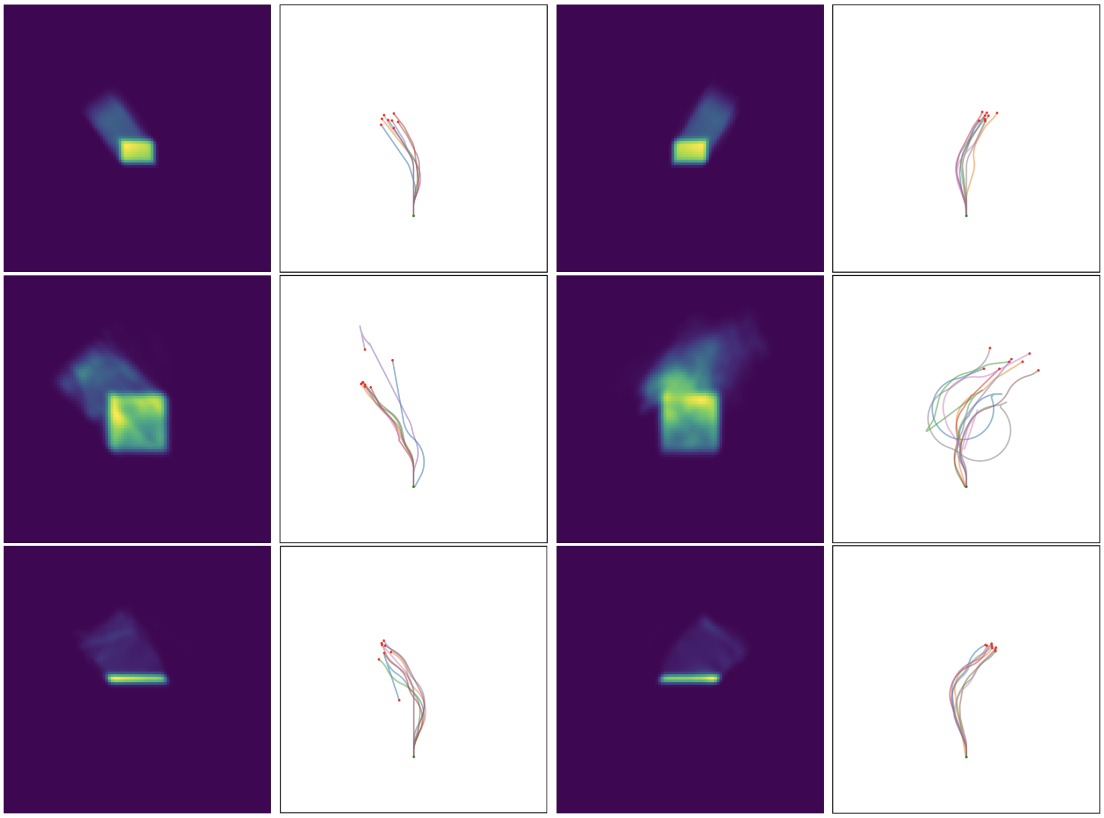

Figure 2: Heatmaps of the object positions (left) and pusher trajectories (right) for the three object categories.

cal objects. This task can be easily extended to encompass a wider variety of scenarios, and is ideally suited for controlled comparisons between humans and computational models.

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