

# Human-like Robot Motion Planning

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**Abstract.** Imagine a robot tasked to grasp an object within a cluttered environment. Currently, most motion planning techniques lack any topdown guidance. We introduce a new planning algorithm based on learning human strategies in such a situation. First, we collect a set of human demonstrations using a virtual reality setup. Then, we abstract the high-level rules learned from these demonstrations using qualitative spatial representations. Finally, such rules are transferred to robot motion planning.

**Keywords:** Human-like computing · Robotics · Motion planning.

## 1 Introduction

Robot motion planning aims to find a collision-free trajectory that satisfies a set of given constraints [1]. Historically, this was posed as a search problem where deterministic methods from state space, dynamics and control theories have been adopted to design motion planners. While these methods managed to plan the motion of low degrees-of-freedom robots, it is very difficult to find a solution in higher-dimensional spaces.

Currently, most planning techniques randomly sample the robots configuration space to find a solution. Sampling-based planners [2] are extensively used with complex and high-dimensional robots. However, such techniques suffer from limited object manipulation ability due to lack of any top-down guidance.

In this work, we introduce a human-like motion planner that tackles the aforementioned problem. More specifically, we aim at extracting the rules underlying the human decision-making strategies. As a practical scenario (Figure 1), imagine a robot tasked to grasp a bottle of milk within a cluttered fridge: how to decide whether to reach directly the goal or firstly push some obstacles away? If deciding to navigate directly, how to generate such a plan? if it is to push an object, which one and where to? We aim at learning answers to these questions from human behaviour and action selection strategies.

## 2 Overall Framework

An overall framework is explained in Figure 2. Using human demonstrations data along with engineered spatial qualitative features, we train classifiers to

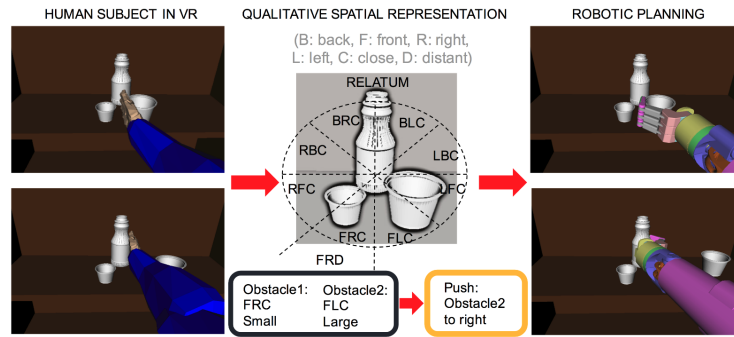


Fig. 1: **Example scenario.** Imagine reaching to grasp a bottle of milk, nestling behind some yogurt pots, within a cluttered fridge. You need to first decide which yogurt pot is best to remove to allow access to the milk bottle, and then generate the appropriate movements to grasp the pot safely.

simulate the human decision-making strategies. For example, a gap-selection classifier can be trained using features like distance from hand, distance from target and shape/size.

### 3 Data Collection

We successfully collected a pilot dataset of human demonstrations performed by five participants who were placed in a virtual room with a table in the middle [3]. The virtual setup provides a tabletop effective work space with dimensions selected to suit human arm movement. An example trial is shown in Figure 3.

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