Learning for Mobile-Robot Error Recovery (Extended Abstract)

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Introduction

Mobile defense, rescue, and space robots are expected to operate in rough and unknown terrain, typically with the aid of human teleoperation. However, teleoperation alone cannot eliminate robots experiencing "locomotion errors," such as when a robot's leg, wheel, or body becoming trapped in a crevice. For example, NASA's Mars rover Spirit became trapped in soft ground and could not be released even after eight months of teleoperated error recovery attempts (Wolchover 2011). Such locomotion errors occur when the robot's circumstances differ from the original design conditions. Indeed, this problem can be further generalized—as robots become more common and operate over long periods (Marder-Eppstein et al. 2010), even personal robots such as the Roomba and the PR2 can be rendered immobile in unpredictable home environments.

When a locomotion error occurs, human operators are required to assist robots by, (1) diagnosing the specific problem and, (2) finding a escape strategy (i.e., a sequence of actions) to release the robot. Current automatic motion planning and control algorithms cannot handle the complex robot-environment physical interactions and dynamic movements required to find an escape route for stuck robots, such as running into obstacles to change the environment, and instead focus on quasi-static and contact-free planning. Our long-term goal is to significantly improve the robustness of mobile-robots by allowing them to autonomously recover from locomotion errors. A learning approach is ideally suited to this problem since the robots are required to extricate themselves from new scenarios about which little information is available *a priori*.

This paper introduces the novel problem of *autonomous mobile-robot error recovery*. First, it will define the mobile-robot error recovery problem and its scope. Second, it enumerates the major challenges faced when tackling this problem. Third, it lays out a generic framework for studying the autonomous mobile-robot error recovery problem.

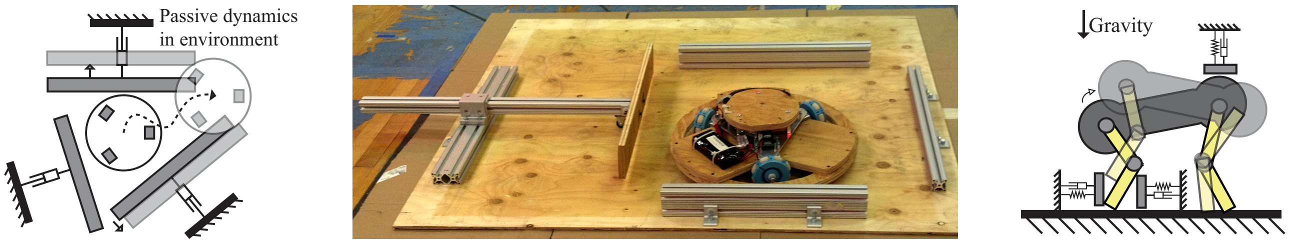
Autonomous Mobile-Robot Error Recovery

There has been little systematic work in the domain of autonomous mobile-robot error recovery. While a classification of locomotion errors has been presented depending on if the error is situational or due to a software or hardware error (Balasubramanian 2006), most prior work focuses on error diagnosis using high-level reasoning techniques on sensor data (Verma, Gordon, and Simmons 2003) or identifies robot components that fail frequently in the field (Carlson and Murphy 2005). There has also been work on human-tuned error recovery gaits, such as uprighting maneuvers (Tunstel 1999) and dynamically coupled locomotion modes (Balasubramanian and Rizzi 2004).

To successfully tackle an instance of the autonomous mobile-robot error recovery problem, a robot must extricate itself from a previously unseen trapped configuration by exploring the environment's affordances and creating an escape by physically interacting with the environment, without human involvement. The robot initially does not know the geometry or affordances of the environment. However, as robot explores the environment, it learns about the affordances of the obstacles it has physically interacted with. Example actions include moving around the environment (if there is sufficient room) or physically interacting with the environment by pushing on obstacles. We assume that the robot can localize itself in the explored environment and keep track of how it has changed the environment. The robot's goal is to incrementally change the environment so that it can escape and resume normal operation.

Challenges

Solving the autonomous mobile-robot error recovery problem is difficult, in part because of the following four reasons. First, the morphology of robot will influence what types of locomotion errors it faces (for example, wheeled and legged robots will encounter different types of problem instances). This is particularly true as the number and variety of deployed robots increases. Second, there are a number of different metrics that could be optimized depending on the particular setting, including minimizing energy use, escape time, or physical (possibly irreversible) damage to the robot or the environment. Third, some situations are difficult even for trained human teleoperators to escape (Sellner et al. 2006), depending on the sensors and affordances available. Fourth, robots are expected to succeed in novel situations, necessitating robust and fast learning.



(a) (b) (c)

Figure 1: a) An omnidirectional robot may be constrained by obstacles in the horizontal plane, b) preliminary omnidirectional robot testbed and c) a schematic where a robot's leg and body are obstructed in the vertical plane

Proposed Framework and Approach

The framework we use to study the mobile-robot error recovery problem includes the following aspects: (1) a representation of the robot and the environment in the locomotion error; (2) an ability to apply learning algorithms to enable the robot to learn to explore its stuck configuration for escape; and (3) an ability to transfer knowledge from past experience to allow past error recovery strategies to improve learning in future scenarios.

Problem Representation: Modeling a robot in a locomotion error requires representing the robot's state r and the environment's state e. Since error recovery may require dynamic maneuvers, the robot and the environment states should include both configuration and velocity. However, in most cases, the robot may be able to choose a suitable action from a state with zero velocity. To reduce the state space dimensionality, the representation will initially only use robot and environment configuration — robot velocity will be included only when needed.

Consider Figures 1a and 1b, where a round omnidirectional robot that is trapped among obstacles that have passive dynamics, such as inertia, elasticity, or viscosity. The robot can move between the obstacles and push them. The robot's state includes the robot's coordinates in the plane, that is, $r = (x_r, y_r)$. Similarly, the environment state e is similarly defined as the set $e = \{(x_{e1}, y_{e1}), \ldots, (x_{en}, y_{en})\}$, where (x_{ei}, y_{ei}) represents the two-dimensional coordinates of the i^{th} obstacle. Initially, we will assume that obstacles move linearly and the state space can be discretized. The representations of r and e would need to be augmented for more complex scenarios, such as for a legged robot in Figure 1c. Dynamics techniques such as Lagrangian and resistance theory (Childress 1981) will allow the robot to evaluate encountered resistance from obstacles as well as the incremental changes it can create in the environment.

Applying Learning Techniques: To achieve autonomous recovery in previously unseen error conditions, we elect to leverage machine learning approaches. By allowing the robot to explore its environment online, full *a priori* knowledge of the environment is not required (e.g., as required by a pure planning approach). Reinforcement learning methods will allow a robot to learn a policy to extricate itself, successfully exploiting the environment's affordances.

Unfortunately, reinforcement learning may be too slow to be practical if each problem instance is considered in isolation. Instead, a robot should leverage its past knowledge to learn better and faster in subsequent error conditions. Our framework aims to accelerate a robot's learning by leveraging techniques such as *transfer learning* (Taylor and Stone 2009) and *options* (Sutton, Precup, and Singh 1999; Konidaris et al. 2010) to allow escape behaviors acquired in one task to improve learning in subsequent tasks.

Concluding Remarks

This paper introduced the autonomous mobile error recovery problem and motivated its importance, as well as discussing initial approaches towards a solution. Our hope is that this paper will engender discussion and enthusiasm for this problem at the intersection of robotics and artificial intelligence.

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