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NAMOSIM: a Robot Motion Planner for Navigation Among Movable Obstacles

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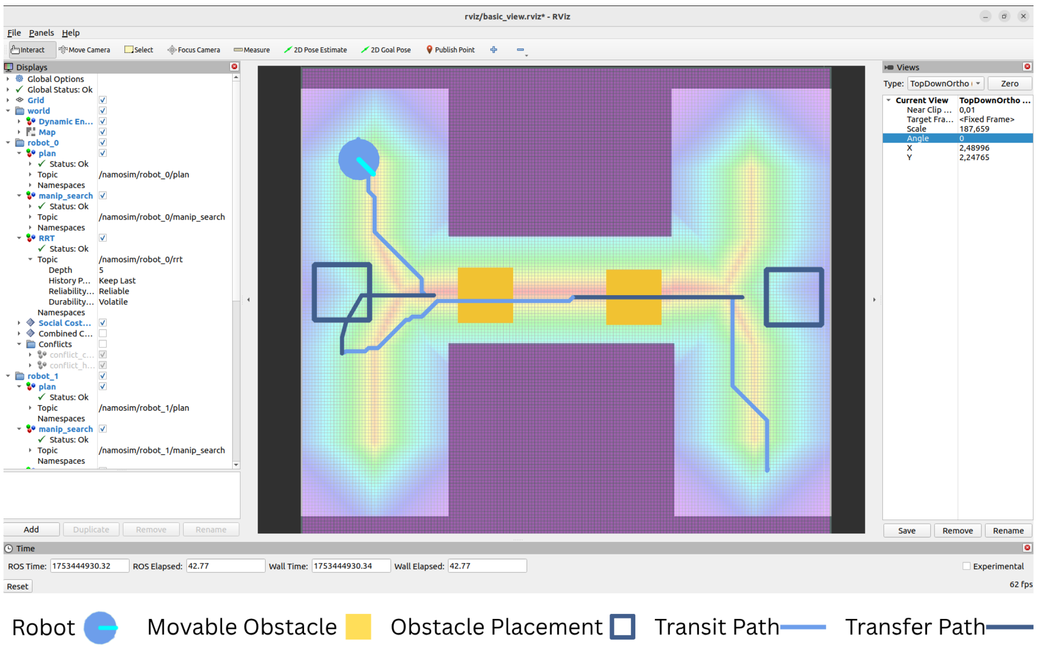

Figure 1: A NAMOSIM scenario with one robot and two obstacles is visualized in RViz. The robot's plan is shown by the blue lines. The darker shade of blue indicates the part of the path involving an obstacle transfer. The empty rectangles indicate the planned obstacle placements. The social costmap is seen in the rainbow background.

Summary

NAMOSIM is a mobile robot motion planner and simulator designed for the problem of **N**avigation **A**mong **M**ovable **O**bstacles (NAMO). The planner simulates robots navigating in 2D polygonal environments where certain obstacles can be grasped and relocated to enable robots to reach their goals. NAMOSIM extends the classic navigation problem with a layer of interactivity, posing interesting research questions while remaining well-defined and amenable to various algorithmic approaches. NAMOSIM is intended for researchers and developers working on robot navigation in dynamic environments, particularly where physical interaction is necessary.

NAMOSIM supports the development of custom NAMO algorithms using a modular agent-based architecture. It includes a baseline agent implementing Stilman's NAMO algorithm (Stilman & Kuffner, 2005) and incorporating a communication-free coordination strategy for multi-robot scenarios (Renault et al., 2024). A variety of other agent behaviors are implemented, and new agents utilizing alternative approaches can be integrated into the planner by implementing the **Agent** base class. NAMOSIM thus supports reproducible research in single and multi-robot NAMO algorithms.

NAMOSIM is packaged as a ROS 2 (Steven Macenski et al., 2022) package to facilite integration with commonly-used robotics tools such as Nav2 (Steve Macenski et al., 2020) and Gazebo (Koenig & Howard, 2004), but it can also be used as a standalone Python module. Simulations are displayed in a Tkinter window and ROS 2 messages are published for more-detailed visualization in RViz (Kam et al., 2015). Several prebuilt scenarios for testing and benchmarking are included. These are stored as SVG files, allowing for convenient creation of custom scenarios using a free SVG editor such as Inkscape.

Statement of Need

Many interesting applications in autonomous mobile robotics involve physical interaction with the environment as well as social coordination with other agents. However, global navigation planners typically assume static environments, leaving complex behaviors to be managed by separate software components, complicating implementation. Ideally, motion planners should be able to reason about physical and social interactions and adapt to changing conditions. NAMOSIM addresses this challenge by providing an open-source planner and simulation environment designed for single and multi-robot NAMO algorithms, which require not only navigation but also reasoning about which obstacles to move, where to move them, and how to coordinate with other agents.

While there are several prior works on NAMO (Levihn et al., 2013, 2014; Scholz et al., 2016; Wu et al., 2010; Zhang et al., 2023), they lack multi-robot capability and do not provide reusable open-source tools designed for real-world deployment on physical robots. There is also a large body of work on multi-agent path finding (MAPF), but this does not consider movable obstacles. Another innovative related work (Baker et al., 2020) involved both multiple agents and movable obstacles, but was not designed for navigation nor for robotics applications. NAMOSIM fills this gap by providing a versatile software package for experimenting with single and multi-robot NAMO algorithms, supporting the robotics community to create more capable and adapative robotic systems.

Major Features

NAMOSIM provides a robust set of features to support research and development in Navigation Among Movable Obstacles (NAMO):

- **Modular Agent-Based Architecture**: The simulator is built around a flexible `Agent` interface, allowing users to implement and test custom NAMO planning algorithms. A baseline NAMO algorithm implementation is available for immediate use and benchmarking.
- **Support for Multiple Robot Models**: NAMOSIM supports both holonomic and differential-drive robot models, enabling realistic simulation of various robotic platforms.
- **ROS 2 Integration**: NAMOSIM forms a ROS 2 package, enabling seamless integration into simulated and physical robotics projects and visualization via RViz.
- **2D Environment Simulation**: The simulator provides a customizable 2D environment where users can define static and movable obstacles, supporting complex scenarios for testing multi-robot coordination strategies and NAMO algorithms.
- **Prebuilt Scenarios and Tests**: NAMOSIM includes several custom scenario files for benchmarking and testing specific situations.
- **Multi-Robot Coordination**: The simulator supports multi-robot scenarios, and our baseline agent implements a communication-free coordination strategy (Renault et al., 2024).

These features make NAMOSIM a versatile tool for prototyping, evaluating, and deploying NAMO algorithms in diverse robotic applications.

Customizable Scenarios

NAMOSIM environments, or **scenarios**, are stored in SVG format and can be edited using any SVG editor, such as Inkscape. The scenario SVG file contains the following key elements:

- The geometry of the static map
- The polygons and orientations of all robots and movable obstacles
- Configuration settings that define the behavior of the environment and robots

The static map can also be included as an image layer within the SVG to conveniently incorporate ROS grid-map images generated by standard mapping tools.

Architecture

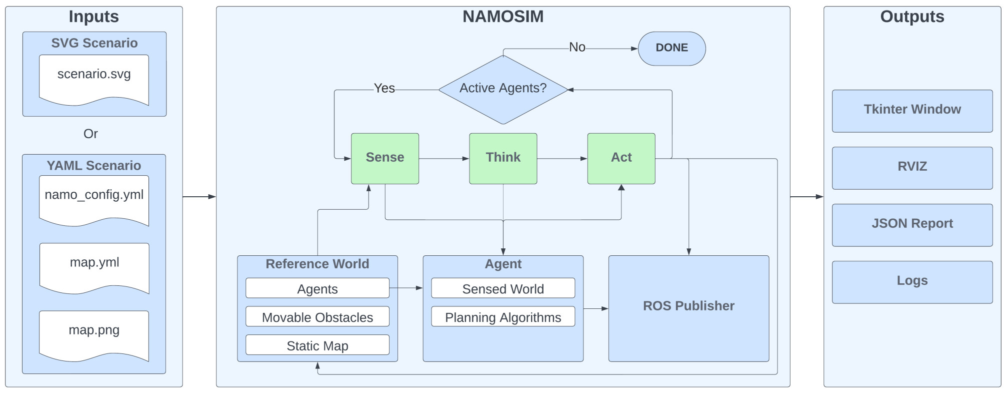

Figure 2: NAMOSIM High-Level Architecture

At a high level, NAMOSIM executes a SENSE-THINK-ACT loop that performs the following functions at each iteration:

1. **SENSE**: Each agent senses the environment and updates its internal representation.
2. **THINK**: Each agent computes a new plan or updates its current plan.
3. **ACT**: Each agent selects a single discrete action to execute.

The loop is expected to execute at a regular frequency, with the assumption that all agent functions run sequentially in a synchronized manner.

Stilman's NAMO Algorithm

NAMOSIM includes a baseline implementation of Stilman's 2005 NAMO algorithm (Stilman & Kuffner, 2005). The key idea of this algorithm is to move obstacles to merge disjoint components of the robot's free configuration space. The map is divided into a set of disjoint **connected components**, where each grid cell in a given component is reachable from all other cells in the same component. It can be proven that components are separated by movable obstacles or are otherwise unreachable. The algorithm functions by moving obstacles to join components until the robot's current component includes the goal cell.

The algorithm works by recursively performing the following two stages:

1. **SELECT_OBSTACLE_AND_COMPONENT**: The first stage performs a simplified A* grid search, allowing the agent to pass through movable obstacles. It returns the ID of the first movable obstacle encountered on the optimal path to the goal and the ID of the component encountered after passing through the obstacle.
2. **OBSTACLE_MANIPULATION_SEARCH**: The second stage finds a **transit path** from the robot's current position to a grasp pose near the obstacle. Then, it finds a **transfer path** by performing an obstacle manipulation search to join the robot's current component to the component selected in stage 1. If this stage fails, the obstacle and component pair are added to an avoid-list, and the algorithm returns to stage 1.

Each iteration of the algorithm continues with a copy of the environment where the robot and obstacle start from the poses resulting from the previous obstacle manipulation search. See also (Renault, 2023) for more details. (Wu et al., 2010) extended Stilman's algorithm to unknown environments where obstacle movability is ascertained through interaction. We hope to implement this idea in NAMOSIM in future work.

Collision Detection

Custom agents are free to implement their own collision detection routines; however, the baseline agent detects collisions using a simple binary-occupancy grid during transit paths (when not carrying an obstacle), assuming a circular robot footprint. When transporting a movable obstacle, the robot footprint is non-circular, and collision detection is based on the **convex swept volume** resulting from the area swept by the combined robot-obstacle footprint due to the action motion (Jiménez et al., 1998). Although computationally expensive, this ensures all possible collisions are detected, regardless of the shape of the robot or obstacle.

Social Costmap

A novel contribution in the baseline implementation is the option to use a social costmap during the obstacle manipulation search to guide obstacle placement decisions. This allows robots to place obstacles in areas less likely to block the free passage of other agents, including humans, reducing the likelihood that obstacles will need to be moved again. The key heuristic of the social costmap is to **avoid narrow corridors and central areas**, assigning higher costs to narrow corridors and the centers of open spaces. This helps robots avoid placing obstacles in front of doorways or in the center of rooms. The social costmap is explained in greater detail in (Renault et al., 2020; Renault, 2023).

Conflict Avoidance and Deadlock Resolution

NAMOSIM's baseline agent can avoid conflicts and resolve deadlocks with other agents. Conflict avoidance works by looking ahead along the agent's current plan for a fixed number of steps, called the **conflict horizon**. Within this horizon, the agent simulates each planned action and checks for potential conflicts. For example, the agent may have planned to move an obstacle that is no longer at the expected location, or another robot may be crossing the planned path within the conflict horizon, raising the potential for a collision.

The baseline agent avoids conflicts by either pausing or replanning around them. A **deadlock** is detected when the same conflict configuration is repeatedly encountered, even after replanning. To resolve deadlocks, the agent follows an evasion strategy which is optionally based on the local social costmap (Renault et al., 2024).

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