Toward Wheeled Mobility on Vertically Challenging Terrain: Platforms, Datasets, and Algorithms

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Most conventional wheeled robots can only move in flat environments and simply divide their planar workspaces into free spaces and obstacles. Deeming obstacles as non-traversable significantly limits wheeled robots' mobility in real-world, non-flat, off-road environments, where part of the terrain (e.g., steep slopes or rugged boulders) will be treated as non-traversable obstacles. Our work is motivated by such limitations and aims at expanding the mobility of these widely available wheeled robot platforms so that they can venture into vertically challenging environments, which would otherwise be deemed as obstacles (non-traversable) or require specialized hardware.

Figure 1: The Verti-Wheelers: Conventional Wheeled Vehicles Moving through Vertically Challenging Terrain.

Thanks to the recent advancement in machine learning, data-driven approaches have been leveraged to improve robot mobility [1]. Learning from data removes the necessity of building analytical models of the environments, such as vehicle-terrain or human-robot interactions, and alleviates the burden of crafting delicate cost functions [2] or tuning unintuitive parameters [3]. Therefore, we hypothesize that data-driven approaches are one avenue toward enabling enhanced wheeled mobility on previously impossible, vertically challenging terrain.

Considering that most ground robots are wheeled with no or passive suspension systems and the potential of machine learning methods, we develop wheeled platforms, large-scale datasets, and both classical and data-driven algorithms to facilitate robot mobility on vertically challenging terrain. We present an open-source design of two wheeled robot platforms, the Verti-Wheelers (VW), which are representative of the majority of existing conventional ground mobile robot platforms, and hypothesize that conventional wheeled robots can also navigate many vertically challenging environments (Figure 1); We identify the following seven desiderata for their hardware and achieve all of them in our design: All-Wheel Drive (D1), Independent Suspensions (D2), Differential Lock (D3), Low/High Gear (D4), Wheel Speed / RPM Sensing (D5), Ground Speed Sensing (D6), Actuated Perception (D7); We collect two datasets to facilitate future data-driven mobility research; We develop three algorithms to autonomously drive wheeled robots over vertically challenging terrain: an Open-Loop (OL), a classical Rule-Based (RB), and a data-driven Behavior Cloning (BC) approach.

For the mechanical components in D1 to D4, we base our platforms on two off-the-shelf, two-axle and four-wheel, three-axle and six-wheel, all-wheel-drive, off-road vehicle chassis from Traxxas. D1 and D2 are therefore achieved. We use an Arduino Mega micro-controller to lock/unlock the front and rear differential (D3) and switch between low and high gear (D4) through three servos. For D5, we install four magnetic sensors on the front and rear axles for our Verti-4-wheeler (V4W) and on the front and middle axles for our Verti-6-Wheeler (V6W), and eight magnets per wheel to sense the wheel rotation. For D6, we install a Crazyflie Flow deck v2 sensor on the chassis facing downward,

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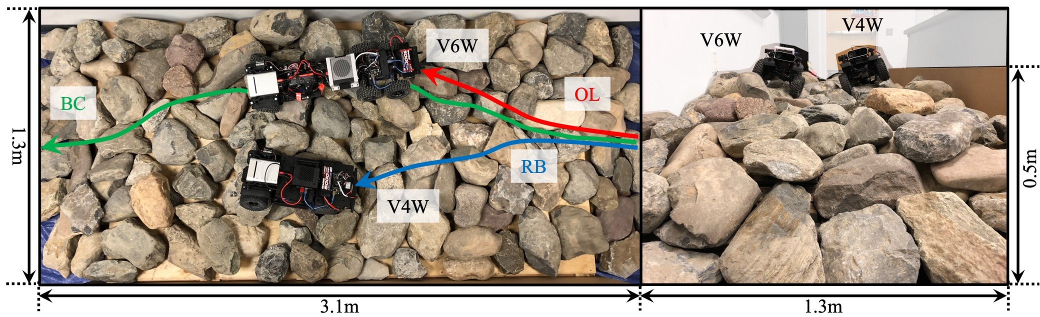

Figure 3: Custom-Built Testbed with V6W and V4W and Example Traversals by the Three Algorithms (OL, RB, and BC).

providing not only 2D ground speed (x and y) but also distance between the sensor and the ground (z). We choose an Azure Kinect RGB-D camera due to its high-resolution depth perception at close range. For D7, we add a tilt joint for the camera actuated by a servo. We use a complementary filter to estimate the camera orientation and a PID controller to regulate the camera pitch angle. We use NVIDIA Jetson AGX Orin and Xavier NX to provide both onboard CPU and GPU computation. To interface all low-level sensors and actuators, we use the Arduino Mega micro-controller. The mechanical and electrical components for both V4W and V6W are shown in Fig. 2

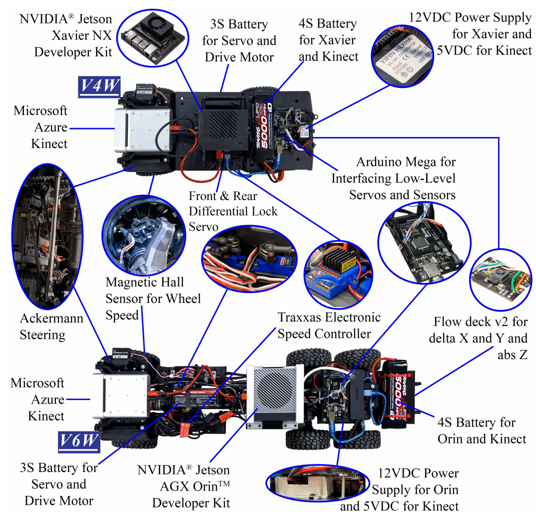

Figure 2: Components of the Verti-Wheelers.

Considering the difficulty in representing surface topography and modeling complex vehicle dynamics and the recent success in data-driven mobility [1], we collect two datasets with the two wheeled robots on our custom-built testbed. We reconfigure our testbed multiple times and both robots are manually driven through different vertically challenging terrain. We collect the following data streams from the onboard sensors and human teleoperation commands: RGB ($1280 \times 720 \times 3$) and depth (512×512) images i, wheel speed w (4D float vector for four wheels), ground speed g (relative movement indicators along Δx and Δy and displacement along z, along with two binary reliability indicators for speeds and displacement), differential release/lock d (2D binary vector for both front and rear differentials), low/high gear switch s (1D binary vector), linear velocity v (scalar float number), and steering angle ω (scalar float number). Each dataset $\mathcal{D}$ is therefore $\mathcal{D} = \{i_t, w_t, g_t, d_t, s_t, v_t, \omega_t\}_{t=1}^{N}$, where N indicates the total number of data frames.

We deploy all three methods, i.e., OL, RB, and BC (BC4 and BC6 learned with the V4W and V6W dataset respectively), on three different test courses (Figure 3). Table 1 reports number of successful trials and mean traversal time with variance. BC4 achieves the best performance among all methods.

Table 1: Number of Successful Trials (Out of 10) and Mean Traversal Time (of Successful Trials in Seconds) with Variance

	V6W				V4W			
	OL	RB	BC6	BC4	OL	RB	BC6	BC4
Easy	5 (20.7 ± 1.7)	8 (19.2 ± 3.9)	9 (13.8 ± 8.2)	**10** (11.6 ± 1.9)	6 (17.7 ± 3.8)	6 (13.4 ± 2.5)	7 (17.2 ± 6.7)	**9** (14.1 ± 7.7)
Medium	6 (15.4 ± 0.9)	9 (14.8 ± 2.2)	9 (14.6 ± 11.2)	**10** (13.6 ± 2.3)	4 (15.6 ± 14.2)	6 (12.9 ± 1.8)	3 (19.2 ± 10.6)	**8** (13.7 ± 1.6)
Difficult	3 (24.1 ± 2.6)	6 (14.3 ± 1.9)	6 (15.7 ± 18.5)	**9** (14.9 ± 2.9)	3 (19.7 ± 29.4)	5 (16.8 ± 20.5)	3 (23.3 ± 43.4)	**7** (14.9 ± 8.2)

During the demonstration session at the workshop, we will showcase our physical VW platforms and demonstrate their autonomous crawling and navigation capability on vertically challenging terrain with a small-scale rock testbed.

References

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