Modeling a Transformable Wheel Mobile Robot With a Simulator Neural Network

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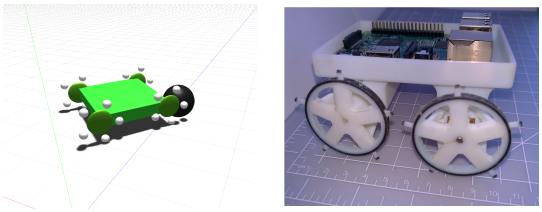
Abstract

It is difficult to model kinematics of a legged-wheel robot. Complex interactions between their irregularly-shaped wheels and the ground make it difficult to derive an accurate mathematical model. Yet, for many applications it is vital to have such a model. For example, to predict the current velocity of the robot. We propose using a neural network to model the kinematics of a transformable wheel mobile robot. We use a physical simulation of our robot to generate training data. The training data is then used to optimize a neural network that can predict changes to the robot's pose based its current control commands. The neural network simulation is better able to predict the location of the physically simulated mobile robot when compared to a differential drive model. Using the trained network, we next evolved a simple controller to navigate a series of way-points. The evolved control parameters were then transferred to the simulated robot where nearly identical behaviors were observed. Our results show that a simulator neural network can be effective in prediction the movement of a transformable wheel mobile robot.

Introduction

Robots are frequently used in remote and unpredictable environments. For example, in *search and rescue* a robot is designed to aid first responders search for victims by traveling over highly varied terrain (Graf et al., 2017). One solution to this problem is to use an unmanned aerial vehicle (UAV). However, UAVs can typically only operate for short periods of time (roughly 30 minutes to one hour).

More recently, lightweight mobile robots with transformable wheels have been developed for search and rescue. As shown in Figure 1, a transformable wheel robot is capable of extending struts radially outward from the center of each wheel. These struts help the robot climb over obstacles that are roughly the same size as the robot (Clark et al., 2018). These devices have the benefits of normal wheels (e.g., increased stability and less vibration) and legged-wheels (e.g., increased mobility), and they have a longer operating duration compared to UAVs.

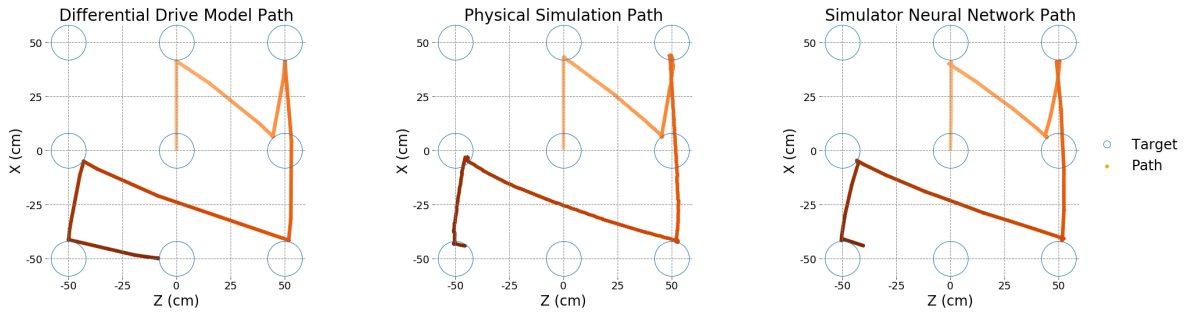


(a) Physical Simulation (b) Prototype

Figure 1: A mobile robot with transformable wheels.

A drawback of using a transformable wheel mobile robot (or a legged-wheel robot) is that they are difficult to model. Without an accurate model of the robot, it is difficult to determine when wheels should be transformed from normal wheels into a legged-wheels. Specifically, a model can be used to calculate the *expected* velocity of the robot, and this quantity can be compared to the *measured* velocity (using sensor readings). If these two quantities differ by some threshold amount, then the robot should infer that it is stuck or slipping (i.e., it is exhibiting poor mobility) and it should extend its wheel struts. Without an accurate model of the robot kinematics, this process cannot work.

Related work. In prior work, we used a differential drive model to calculate *expected* velocity (Clark et al., 2018). This process was error prone. The model did not account for strut extension, wheel slippage (i.e., differing friction properties of different terrains), uneven ground, or that the wheels might rotate at a different rate than commanded. In this study, we develop a simulator neural network (SNN) similar to that described by Pretorius et al. (2014), where they train a neural network so that control signals map to changes the the pose of the robot. The goal of this study is to produce an accurate model of our mobile robot. The model will have two uses: (1) to act in place of a physical simulation for optimizing control parameters and (2) to determine when the robot exhibits poor mobility and should extend struts.



(a) (b) (c)

Figure 2: Example paths taken by the robot (a) as predicted by the differential drive model, (b) during a physical simulation, and (c) as predicted by a trained SNN. Blue circles indicated way-points that the robot is trying to reach in a predefined sequence. The robot moves on to its next way-point once it gets within 10cm of the current way-point. Paths are indicated in orange, and lighter shades indicate earlier an earlier time (the robot starts at the origin).

Training a Simulator Neural Network

The goal of our study is to develop a SNN that is able to determine a new pose for our mobile robot based on the input control signals. To train the neural network, we first need some way to collect training data.

Collecting training data. We built a physical simulation of our robot using DART (Lee et al., 2018). The simulation can be run with different values for the robot's input control signals: the speeds of the left and right wheels as well as the strut extension amount. The simulation did not include any obstacles or uneven terrain. We ran the simulation with 9012 different combinations of these input signals and collected the resulting change in position and heading.

Training the SNN. The SNN comprises three neural networks, one for predicting the change in longitudinal position, one for lateral position, and one for heading. We evaluated several different neural network hyperparameters (i.e., architectures, optimization algorithms, learn rates, etc.). We achieved the highest accuracy on our validation data when using a network with two hidden layers, each with 20 nodes, and the L-BFGS optimizer with an adaptive learning rate.

Comparing the SNN model. Figure 2 shows paths of a robot as dictated by the differential drive model, the physical simulation, and our trained neural networks. As shown in the figure, the SNN more closely resembles the actual path of the simulated robot when compared to the kinematics model. Other example paths (using different control parameters) showed similar relative performances. Thus, the SNN is a more accurate model of the physical simulation. The SNN outperforms the differential drive model because it takes into account the wheel extensions and slippage. Since the SNN takes into account these physical properties and limitations, and the real world has even more sources of noise and external influence, we expect the relative accuracy of the SNN to be even higher when these experiments are performed with our physical device.

Evolving a simple controller. As the SNN is an accruate model of the physical simulation, we next attempted to use the SNN to optimize a simple controller for performing the way-point following task (as shown in Figure 2). An advantage of using the SNN is that it is approximately 30 times faster than the physical simulation. Thus on a standard laptop, optimizing a simple finite state machine with differential evolution took only two minutes, whereas it would have taken one hour using our physical simulation. An interactive visualization of the way-point following robot can be found at this address: `http://bit.ly/2ChVuqr`.

Conclusions. As previously stated, we have two goals for the SNN: (1) to act in place of a physical simulation and (2) to detect poor mobility and dictate when wheel struts should be extended. In this study, we have shown that goal (1) is attainable by evolving the parameters of a simple controller for way-point following. In our future work, we will use the trained SNN to detect poor mobility when the robot is operating in an environment with obstacles and uneven terrain.

References

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