Using Neural Networks to Learn Quadruped Leg Models

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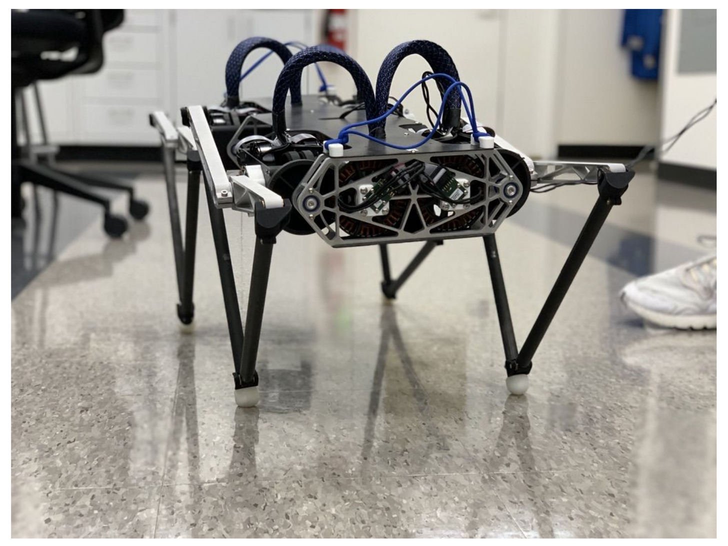
Introduction

- Stanford Robotics has built a set of highly capable quadruped robots
- Knowledge of estimated contact force would improve state estimation accuracy



- Force sensors are expensive and can often give inaccurate results
- The leg transmissions are quasi direct drive (QDD), which allows accurate force measurements through just proprioception
- Traditional physics based model don't handle complex non-linear factors like friction very easily
- A neural network would be able to model these complications more easily and output accurate contact forces

Related Work

- Smith et al. implemented an Inverse Dynamics based Neural Network (IDNN) in order to learn a mapping from joint measurements to "free torques" (which is converted to forces via the Jacobian) [1]
- Camurri et al. implemented a used Recursive Newton Euler algorithms to estimate "free torque" and observe contact [2]

Problem Formulation

- The dynamics of the legs can be written via the Manipulator equation as follows:

$$\tau + J^T F_{ext} = D(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + F(\dot{q})$$
$$= \tau_{free}$$

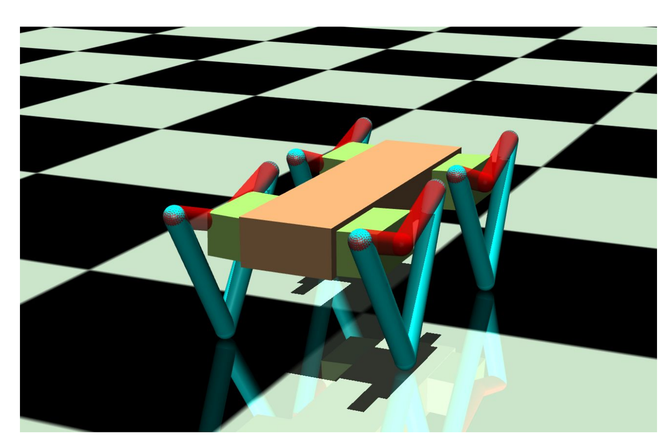
- This means that the external force on the legs can be written as simply:

$$F_{ext} = J^{-T}\left(\tau_{free} - \tau\right)$$

- Following the approach of Smith et al., the neural network will try and learn a mapping from joint measurements to "free torque"
- The Jacobian is a simply (and accurately) derived through kinematics

Data Collection

- All training and testing data was collected using MuJoCo, a physics simulator that models contact
- Learning of model of the free torques greatly simplifies the collection of training data
- Data was collected inside the space of leg positions, velocities, and torques that will be seen during operation
- Data was collected while the leg was controlled to random leg positions with traditional controls



Results

- Simple linear regression failed to model the data well which makes sense because of the non-linear nature of the Manipulator equation
- Just using joint position and velocity results in an extremely poor fit for the data
- For this reason, using a history of joint position and velocity measurements results in a much better fit for the data
- Ideally, measurements of joint acceleration would be inputted to the network, but there is no joint acceleration sensor on the physical robot

Conclusion

- Providing a history of joint position and velocity data resulted in a reasonably good fit for the data
- In order to actually implement this on the real robot, real data collected from hardware must be used to train the network
- By using this model structure, a force sensor is only need to validate the accuracy of the force output but not to train the network

References

[1] Smith, A.C., Mobasser, F. and Hashtrudi-Zaad, K., 2006. Neural-network-based contact force observers for haptic applications. *IEEE Transactions on Robotics*, *22*(6), pp.1163-1175.

[2] Camurri, M., Fallon, M., Bazeille, S., Radulescu, A., Barasuol, V., Caldwell, D.G. and Semini, C., 2017. Probabilistic contact estimation and impact detection for state estimation of quadruped robots. *IEEE Robotics and Automation Letters*, *2*(2), pp.1023-1030.