

Torque-limited Simple Pendulum: Reference

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CHAPTER ONE

INTRODUCTION

1.1 Documentation

In this reference you will find installation and usage guides to get going with a real system, as well as dives into:

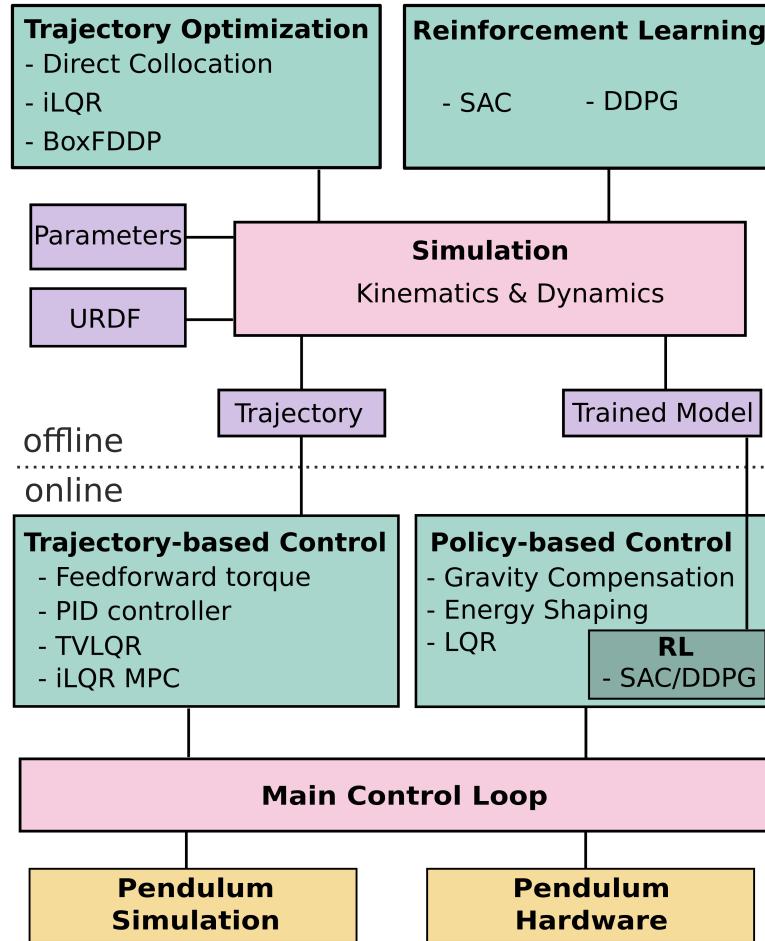
- Code testing
- The physics of a simple pendulum
- Our hardware and test bench
- Motor configuration

We've additionally uploaded all CAD files to grabcad.com: you can use its 3D viewer to display the 3D model directly within your browser.

A range of methods to solve the control problem will then be presented. Their implementation will be discussed, as well as their advantages and disadvantages observed experimentally.

Lastly you will find the API reference of the `simple_pendulum` package, including all functions available within it.

1.2 Overview of Methods



Trajectory Optimization tries to find a trajectory of control inputs and states that is feasible for the system while minimizing a cost function. The cost function can for example include terms which drive the system to a desired goal state and penalize the usage of high torques. The following trajectory optimization algorithms are implemented:

- **Direct Collocation:** A collocation method, which transforms the optimal control problem into a mathematical programming problem which is solved by sequential quadratic programming. For more information, click [here](#)
- **Iterative Linear Quadratic Regulator (iLQR):** A optimization algorithm which iteratively linearizes the system dynamics and applies LQR to find an optimal trajectory. For more information, click [here](#)
- **Feasibility driven Differential Dynamic Programming (FDDP):** Trajectory optimization using locally quadratic dynamics and cost models. For more information about DDP, click [here](#) and for FDDP, click [here](#)

The optimization is done with a simulation of the pendulum dynamics.

Reinforcement Learning (RL) can be used to learn a policy on the state space of the robot, which then can be

used to control the robot. The simple pendulum can be formulated as a RL problem with two continuous inputs and one continuous output. Similar to the cost function in trajectory optimization, the policy is trained with a reward function. The following RL algorithms are implemented:

- **Soft Actor Critic (SAC)**: An off-policy model free reinforcement learning algorithm. Maximizes a trade-off between expected return of a reward function and entropy, a measure of randomness in the policy. For more information, click [here](#)
- **Deep Deterministic Policy Gradient (DDPG)**: An off-policy reinforcement algorithm which concurrently learns a Q-function and uses this Q-function to train a policy in the state space. For more information, click [here](#).

Both methods, are model-free, i.e. they use the dynamics of the system as a black box. Currently, learning is possible in the simulation environment.

Trajectory-based Controllers act on a precomputed trajectory and ensure that the system follows the trajectory properly. The trajectory-based controllers implemented in this project are:

- **Feed-forward torque Controller**: Simple forwarding of a control signal from a precomputed trajectory.
- **Proportional-Integral-Derivative (PID)**: A controller reacting to the position error, integrated error and error derivative to a precomputed trajectory.
- **Time-varying Linear Quadratic Regulator (tvLQR)**: A controller which linearizes the system dynamics at every timestep around the precomputed trajectory and uses LQR to drive the system towards this nominal trajectory.
- **Model predictive control with iLQR**: A controller which performs an iLQR optimization at every timestep and executes the first control signal of the computed optimal trajectory.

Feedforward and PID controller operate model independent, while the TVLQR and iLQR MPC controllers utilize knowledge about the pendulum model. In contrast to the others, the iLQR MPC controller optimizes over a predefined horizon at every timestep.

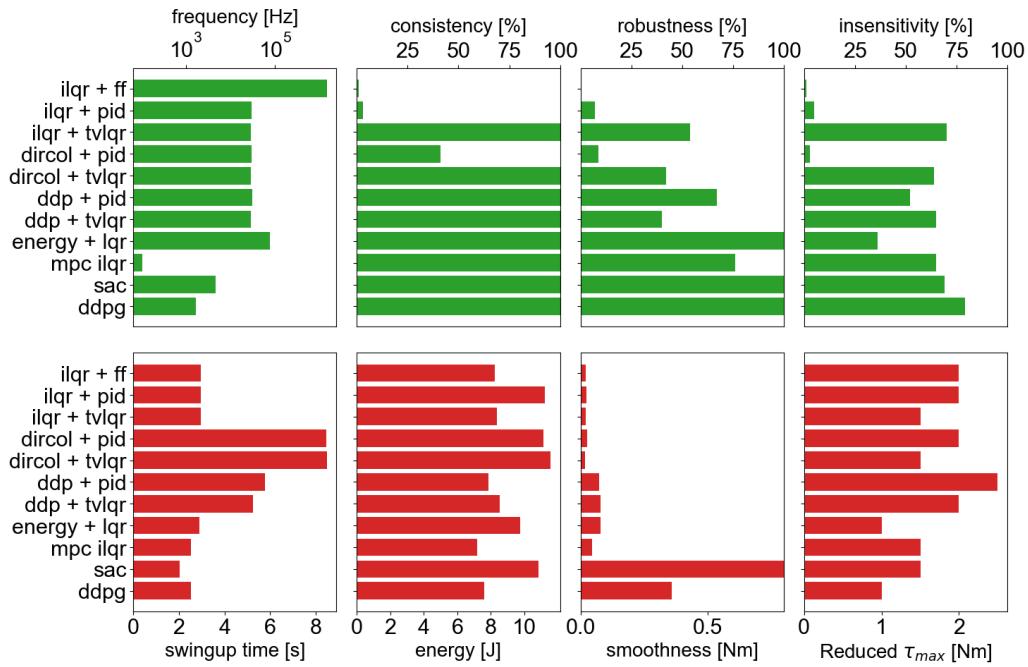
Policy-based Controllers take the state of the system as input and output a control signal. In contrast to trajectory optimization, these controllers do not compute just a single trajectory. Instead, they react to the current state of the pendulum and because of this they can cope with perturbations during the execution. The following policy-based controllers are implemented:

- **Gravity Compensation**: A controller compensating the gravitational force acting on the pendulum. The pendulum can be moved as if it was in zero-g.
- **Energy Shaping**: A controller regulating the energy of the pendulum. Drives the pendulum towards a desired energy level.
- **Linear Quadratic Regulator (LQR)**: Linearizes the dynamics around a fixed point and drives the pendulum towards the fixpoint with a quadratic cost function. Only useable in a state space region around the fixpoint.

All of these controllers utilize model knowledge. Additionally, the control policies, obtained by one of the RL methods, fall in the category of policy-based control.

The implementations of direct collocation and TVLQR make use of [drake](#), iLQR makes use of the symbolic library of drake or sympy, FDDP makes use of [Crocoddyl](#), SAC uses the [stable-baselines3](#) implementation and DDPG is implemented in [Tensorflow](#). The other methods use only standard libraries.

The controllers can be benchmarked in simulation with a set of predefined criteria.



1.3 Authors

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Hardware Maintainer:

- Jonathan Babel

Contributors:

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- Heiner Peters
- Shubham Vyas
- Melya Boukheddimi
- Mihaela Popescu

Feel free to contact us if you have questions about the test bench. Enjoy!

1.4 Contributing

1. Fork it
2. Create your feature branch:

```
git checkout -b feature/fooBar
```

3. Commit your changes:

```
git commit -am 'Add some fooBar'
```

4. Push to the branch:

```
git push origin feature/fooBar
```

5. Create a new Pull Request

See [How to Contribute](#) for more details.

1.5 Safety Notes

When working with a real system be careful and mind the following safety measures:

- Brushless motors can be very powerful, moving with tremendous force and speed. Always limit the range of motion, power, force and speed using configurable parameters, current limited supplies, and mechanical design.
- Stay away from the plane in which pendulum is swinging. It is recommended to have a safety net surrounding the pendulum in case the pendulum flies away.
- Make sure you have access to emergency stop while doing experiments. Be extra careful while operating in pure torque control loop.

1.6 Acknowledgements

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1.7 License

This work has been released under the BSD 3-Clause License. Details and terms of use are specified in the LICENSE file within this repository. Note that we do not publish third-party software, hence software packages from other developers are released under their very own terms and conditions, e.g. Stable baselines (MIT License) and Tensorflow (Apache License v2.0). If you install third-party software packages along with this repo ensure that you follow each individual license agreement.

1.8 Citation

Felix Wiebe, Jonathan Babel, Shivesh Kumar, Shubham Vyas, Daniel Harnack, Melya Boukheddimi, Mihaela Popescu, Frank Kirchner. Torque-limited simple pendulum: A toolkit for getting familiar with control algorithms in underactuated robotics. In: Journal of Open Source Software (JOSS) (submitted).

CHAPTER TWO

INSTALLATION GUIDE

In order to execute the python code within the repository you will need to have *Python (>=3.6, <4)* along with the package installer *pip3* on your system installed.

- **python (>=3.6, <4)**
- **pip3**

If you aren't running a suitable python version currently on your system, we recommend you to install the required python version inside of an virtual environment for python (**pyenv**) and to install all python packages necessary to use this repo afterwards inside a newly created virtual environment (**virtualenv**). The installation procedure for Ubuntu (18.04.5 and 20.04.2.0 LTS) are described in the next section. You can find instructions for MacOS and other Linux distributions, as well as information about common build problems here:

- **pyenv:** <https://github.com/pyenv/pyenv>
- **virtualenv:** <https://github.com/pyenv/pyenv-virtualenv>

2.1 Installing this Python Package

If you want to install this package with your system python version, you can do that by going to the directory `software/python` and typing:

```
pip install .
```

Note: This has to be repeated if you make changes to the code (besides the scripts).

2.2 Instructions for Ubuntu (18.04.5 and 20.04.2.0 LTS)

The instructions provide assistance in the setup procedure, but with regards to the software **LICENSE** they are provided without warranty of any kind. In no event shall the authors or copyright holders be liable for any claim, damages or other liability, arising from, out of or in connection with the software or the use or other dealings in the software.

1. Clone this repo from GitHub, in case you haven't done it yet:

```
git clone git@github.com:dfki-ric-underactuated-lab/torque_limited_simple_
↪pendulum.git
```

2. Check your Python version with:

```
python3 --version
```

If you are already using suitable Python 3.6 version jump directly to step *Creating a Virtual Environment* otherwise continue here and first install a virtual environment for python.

2.3 Pyenv: Virtual environment for Python

The following instructions are our recommendations for a sane build environment.

1. Make sure to have installed python's binary dependencies and build tools as per:

```
sudo apt-get update
sudo apt-get install make build-essential libssl-dev zlib1g-dev
libbz2-dev libreadline-dev libsqlite3-dev wget curl llvm
libncursesw5-dev xz-utils tk-dev libxml2-dev libxmlsec1-dev libffi-dev_
↪liblzma-dev
```

2. Once prerequisites have been installed correctly, install Pyenv with:

```
curl https://pyenv.run | bash
```

3. Configure your shell's environment for Pyenv

Note: The below instructions are designed for common shell setups. If you have an uncommon setup and they don't work for you, use the linked guidance to figure out what you need to do in your specific case: <https://github.com/pyenv/pyenv#advanced-configuration>

Before editing your *.bashrc* and *.profile* files it is a good idea to <ins>make a copy</ins> of both files in case something goes wrong. Add pyenv to your *.bashrc* file from the terminal:

```
echo 'eval "$(pyenv init -)"' >> ~/.bashrc
```

Add these lines at the beginning of your *.profile* file (not from the terminal):

```
export PYENV_ROOT="$HOME/.pyenv"
export PATH="$PYENV_ROOT/bin:$PATH"
```

and this line at the very end of your *.profile* file (not from the terminal):

```
eval "$(pyenv init --path)"
```

4. Source *.profile* and *.bashrc*, then restart your shell so the path changes take effect:

```
source ~/.profile
source ~/.bashrc

exec $SHELL
```

5. Run `pyenv init -` in your shell, then copy and also execute the output to enable shims:

```
pyenv init -
```

Restart your login session for the changes to take effect. If you're in a GUI session, you need to fully log out and log back in. You can now begin using pyenv.

Note: Consider upgrading to the latest version of Pyenv via:

```
pyenv update
```

2.4 Installing Python into Pyenv

You can display a list of available Python versions with:

```
pyenv install -l | grep -ow [0-9].[0-9].[0-9]
```

Install your desired Python version using Pyenv (We suggest 3.6.9 for ubuntu 18.04 and 3.8.10 for ubuntu 20.04):

```
pyenv install 3.x.x
```

Double check your work:

```
pyenv versions
```

To use Python 3.x only for this specific project change directory to the cloned git repo and type:

```
pyenv local 3.x.x
```

2.5 Creating a Virtual Environment with Pyenv

In order to clutter your system as little as possible all further packages will be installed inside a virtual environment, which can be easily removed at any time. The recommended way to configure your own custom Python environment is via *Virtualenv*.

1. Clone virtualenv from <https://github.com/pyenv/pyenv-virtualenv> into the pyenv-plugin directory:

```
git clone https://github.com/pyenv/pyenv-virtualenv.git $(pyenv root) /
  ↳plugins/pyenv-virtualenv
```

2. Add pyenv virtualenv-init to your shell to enable auto-activation of virtualenvs:

```
echo 'eval "$(pyenv virtualenv-init -)"' >> ~/.bashrc
```

3. Restart your shell to enable pyenv-virtualenv:

```
exec "$SHELL"
```

4. To create a new virtual environment, e.g. named simple-pendulum with Python 3.6.9 run:

```
pyenv virtualenv 3.6.9 simple-pendulum
```

5. Activate the new virtual environment with the command:

```
pyenv activate simple-pendulum
```

The name of the current virtual environment (*venv*) appears to the left of the prompt, indicating that you are now working inside a virtual environment. When finished working in the virtual environment, you can deactivate it by running the following:

```
pyenv deactivate
```

In case that you don't need the virtual environment anymore, you can deactivate it and remove it together with all previously installed packages:

```
pyenv uninstall simple-pendulum
```

2.6 Installing pip3

Update the package list inside your recently created virtual environment:

```
sudo apt update
```

and install pip3 via:

```
sudo apt install python3-pip
```

If you like, you can update pip and verify your the installation by:

```
pip install --upgrade pip
pip3 --version
```

2.7 Install Requirements for this Repository

Navigate inside your cloned git repo to `/torque_limited_simple_pendulum/software/python` and make sure your virtual environment is active `pyenv activate simple-pendulum`. Now you can install version specific packages for all required packages from the `requirements.txt` file via:

```
python3 -m pip install -r requirements.txt
```

Note:

1. You can generate your own `requirements.txt` file with this command: `pip freeze > requirements.txt`
 2. You can skip this step and directly install this package with the `setup.py` file as described in the next line. This will install the requirement packages as well. The `setup.py` will not install specific versions of the requirements, that have been tested by us, but instead, it will install the latest version.
-

This package then can be installed from the `software/python` directory by typing:

```
pip install .
```

This was the final installation step. Your system is now prepared to run all code snippets from this repo (except the ones which require [Crocoddyl](#), see next section for instructions). Have fun exploring all kind of different simple pendulum controllers!

2.8 OPTIONAL: Crocoddyl and Gepetto Viewer

For installing the optimal control library Crocoddyl, we refer to the instructions provided in the [Crocoddyl github repository](#) and recommend the installation through `robotpkg`.

[Crocoddyl](#) has an interface to the gepetto-viewer for visualization. For installing the gepetto viewer we refer to their [github repository](#).

CHAPTER THREE

USAGE INSTRUCTIONS

3.1 Installing Python Driver for T-Motor AK80-6 Actuator

1. Clone the python motor driver from: <https://github.com/dfki-ric-underactuated-lab/mini-cheetah-tmotor-python-can>
2. Modify the `.bashrc` file to add the driver to your python path. Make sure you restart your terminal after this step.:

```
# mini-cheetah driver
export PYTHONPATH=~/path/from/home/to/underactuated-robotics/python-motor-
→driver:${PYTHONPATH}
```

Make sure you setup your can interface first. The easiest way to do this is to run `sh setup_caninterface.sh` from the `mini-cheetah-motor/python-motor-driver` folder. To run an offline computed swingup trajectory, use: `python3 swingup_control.py`. The script assumes can id as '`can0`' and motor id as `0x01`. If these parameters differ, please modify them within the script. Alternatively, the motor driver can also be installed via pip from <https://pypi.org/project/mini-cheetah-motor-driver-socketcan/>:

```
pip install mini-cheetah-motor-driver-socketcan
```

3.2 Setting up the CAN interface

1. Run this command and make sure that `can0` (or any other can interface depending on the system) shows up as an interface after connecting the USB cable to your laptop: `ip link show`
2. Configure the `can0` interface to have a 1 Mbaud communication frequency: `sudo ip link set can0 type can bitrate 1000000`
3. To bring up the `can0` interface, run: `sudo ip link set up can0`

Note: Alternatively, one could run the shell script `setup_caninterface.sh` which will do the job for you.

4. To change motor parameters such as CAN ID or to calibrate the encoder, a serial connection is used. The serial terminal GUI used on linux for this purpose is *cuteCom*

3.3 Testing Communication

To enable one motor at *0x01*, set zero position and disable the motor, run: *python3 can_motorlib_test.py can0 → 5*

Use in Scripts: Add the following import to your python script: *from canmotorlib import CanMotorController* after making sure this folder is available in the import path/PYTHONPATH.

Example Motor Initialization:

```
`motor = CanMotorController(can_socket='can0', motor_id=0x01, socket_timeout=0.5)`
```

Available Functions:

- *enable_motor()*
- *disable_motor()*
- *set_zero_position()*
- *send_deg_command(position_in_degrees, velocity_in_degrees, Kp, Kd, tau_ff):*
- *send_rad_command(position_in_radians, velocity_in_radians, Kp, Kd, tau_ff):*

All functions return current position, velocity, torque in SI units except for *send_deg_command*.

Performance Profiler: Sends and received 1000 zero commands to measure the communication frequency with 1/2 motors. Be careful as the motor torque will be set to zero.

3.4 Using different Controllers for the Swing-Up

All implemented controllers can be called from the *main.py* file. The desired controller is selected via a required flag, e.g. if you want to execute the gravity compensation experiment the corresponding command would then be:

```
python main.py -gravity
```

Make sure you execute the command from the directory */software/python/examples_real_system* otherwise you have to specify the path to *main.py* as well. If you want to autosave all data from your experiment use the optional flag *-save* together with the flag required for the controller.

To get an overview of all possible arguments display help documentation via:

```
python main.py -h
```



3.5 Saving Results

The results folder serves as the directory, where all results generated from the python code shall be stored. The distinct separation between python script files and generated output files helps to keep the python package clear and tidy. We provide some example output data from the very start, so that you may see what results each script produces even before you run the code. The tools to create result files from the respective experiment data are located within the python package under */utilities*, *plot.py*, *plot_policy.py* and *process_data.py*.

In general particular functions get called from *main.py* or another script to produce the desired output, which improves resuability of the utilities and keeps the code concise. The results of each experiment are saved in a new folder, which is automatically assigned a timestamp and an appropriate name.

CHAPTER
FOUR

HOW TO TEST THE CODE

For verifying the functionality of the python code, first install [pytest](#) via:

```
pip install -U pytest
```

Note: If you install pytest inside a virtual environment, you have to deactivate and then reactivate the environment for pytest to be used in the virtual environment.

Every trajectory optimization algorithm and every controller in this software package has a unit_test.py file which verifies the functionality of the corresponding piece of software. The pendulum plant has a unit_test.py script as well.

pytest automatically identifies all python scripts with names `*_test.py` or `test_*.py` in the current directory and all subdirectories. Therefore, if you want to perform all unit tests in this software package, simply go to the [python root directory](#) and type:

```
python -m pytest
```

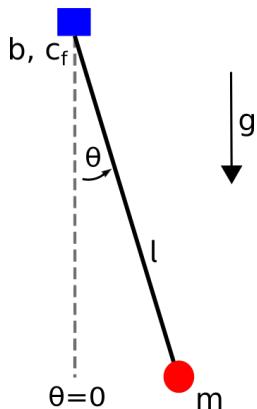
If you want perform a specific unit test (e.g. for the lqr controller) use:

```
pytest software/python/controller/lqr/unit_test.py
```

THE PHYSICS OF A SIMPLE PENDULUM

5.1 Equation of Motion

$$I\ddot{\theta} + b\dot{\theta} + c_f \text{sign}(\dot{\theta}) + mgl \sin(\theta) = \tau$$



where

- θ , $\dot{\theta}$, $\ddot{\theta}$ are the angular displacement, angular velocity and angular acceleration of the pendulum. $\theta = 0$ means the pendulum is at its stable fixpoint (i.e. hanging down).
- I is the inertia of the pendulum. For a point mass: $I = ml^2$
- m mass of the pendulum
- l length of the pendulum
- b damping friction coefficient
- c_f coulomb friction coefficient
- g gravity (positive direction points down)
- τ torque applied by the motor

The pendulum has two fixpoints, one of them being stable (the pendulum hanging down) and the other being unstable (the pendulum pointing upwards). A challenge from the control point of view is to swing the pendulum up to the unstable fixpoint and stabilize the pendulum in that state.

5.2 Energy of the Pendulum

- Kinetic Energy (K)

$$K = \frac{1}{2}ml^2\dot{\theta}^2$$

- Potential Energy (U)

$$U = -mgl \cos(\theta)$$

- Total Energy (E)

$$E = K + U$$

5.3 PendulumPlant

The PendulumPlant class contains the kinematics and dynamics functions of the simple, torque limited pendulum.

The pendulum plant can be initialized as follows:

```
pendulum = PendulumPlant(mass=1.0,
                           length=0.5,
                           damping=0.1,
                           gravity=9.81,
                           coulomb_fric=0.02,
                           inertia=None,
                           torque_limit=2.0)
```

where the input parameters correspond to the parameters in the equation of motion (1). The input inertia=None is the default and the inertia is set to the inertia of a point mass at the end of the pendulum stick $I = ml^2$. Additionally, a torque_limit can be passed to the class. Torques greater than the torque_limit or smaller than -torque_limit will be cut off.

The plant can now be used to calculate the forward kinematics with:

```
[[x, y]] = pendulum.forward_kinematics(pos)
```

where pos is the angle θ of interest. This function returns the (x,y) coordinates of the tip of the pendulum inside a list. The return is a list of all link coordinates of the system (as the pendulum has only one, this returns [[x,y]]).

Similarly, inverse kinematics can be computed with:

```
pos = pendulum.inverse_kinematics(ee_pos)
```

where ee_pos is a list of the end_effector coordinates [x,y]. pendulum.inverse_kinematics returns the angle of the system as a float.

Forward dynamics can be calculated with:

```
accn = pendulum.forward_dynamics(state, tau)
```

where state is the state of the pendulum [$\theta, \dot{\theta}$] and tau the motor torque as a float. The function returns the angular acceleration.

For inverse kinematics:

```
tau = pendulum.inverse_kinematics(state, accn)
```

where again state is the state of the pendulum [$\theta, \dot{\theta}$] and accn the acceleration. The function return the motor torque τ that would be neccessary to produce the desired acceleration at the specified state.

Finally, the function:

```
res = pendulum.rhs(t, state, tau)
```

returns the integrand of the equaitons of motion, i.e. the object that can be calculated with a time step to obtain the forward evolution of the system. The API of the function is written to match the API requested inside the simulator class. t is the time which is not used in the pendulum dynamics (the dynamics do not change with time). state again is the pendulum state and tau the motor torque. res is a numpy array with shape np.shape(res)=(2,) and $\text{res} = [\dot{\theta}, \ddot{\theta}]$.

5.3.1 Usage

The class is inteded to be used inside the simulator class.

5.3.2 Parameter Identification

The rigid-body model derived from a-priori known geometry as described previously has the form

$$\tau(t) = \mathbf{Y}(\theta(t), \dot{\theta}(t), \ddot{\theta}(t)) \lambda$$

where actuation torques τ , joint positions $\theta(t)$, velocities $\dot{\theta}(t)$ and accelerations $\ddot{\theta}(t)$ depend on time t and $\lambda \in \mathbb{R}^{6n}$ denotes the parameter vector. Two additional parameters for Coulomb and viscous friction are added to the model, $F_{c,i}$ and $F_{\{v,i\}}$, in order to take joint friction into account. The required torques for model-based control can be measured using stiff position control and closely tracking the reference trajectory. A sufficiently rich, periodic, band-limited excitation trajectory is obtained by modifying the parameters of a Fourier-Series as described by [^fn3]. The dynamic parameters $\hat{\lambda}$ are estimated through least squares optimization between measured torque and computed torque

$$\hat{\lambda} = \underset{\lambda}{\operatorname{argmin}} ((\lambda - \tau_m)^T (\lambda - \tau_m)),$$

where τ_m denotes the identification matrix.

5.3.3 References

- **Bruno Siciliano et al.** *Robotics*. Red. by Michael J. Grimble and Michael A. Johnson. Advanced Textbooks in Control and Signal Processing. London: Springer London, 2009. ISBN: 978-1-84628-641-4 978-1-84628-642-1. DOI: 10.1007/978-1-84628-642-1 (visited on 09/27/2021).
- **Vinzenz Bargsten, José de Gea Fernández, and Yohannes Kassahun.** *Experimental Robot Inverse Dynamics Identification Using Classical and Machine Learning Techniques*. In: ed. by International Symposium on Robotics. OCLC: 953281127. 2016. (visited on 09/27/2021).
- **Jan Swevers, Walter Verdonck, and Joris De Schutter.** *Dynamic ModelIdentification for Industrial Robots*. In: IEEE Control Systems27.5 (Oct.2007), pp. 58–71. ISSN: 1066-033X, 1941-000X.doi:10.1109/MCS.2007.904659 (visited on 09/27/2021).

CHAPTER SIX

HARDWARE SETUP

6.1 Motor Configuration

The R-LINK Configuration Tool is used to configure the AK80-6 from T-Motors. Before starting to use the R-Link device make sure you have downloaded the *CP210x Universal Windows Driver* from silabs. If this isn't working properly follow the instructions at sparkfun on how to install ch340 drivers. You have to download the *CH341SER (EXE)* file from the sparkfun webpage. Notice that you first have to select uninstall in the CH341 driver menu to uninstall old drivers before you are able to install the new driver. The configuration tool software for the R-LINK module can be downloaded on the T-Motors website.

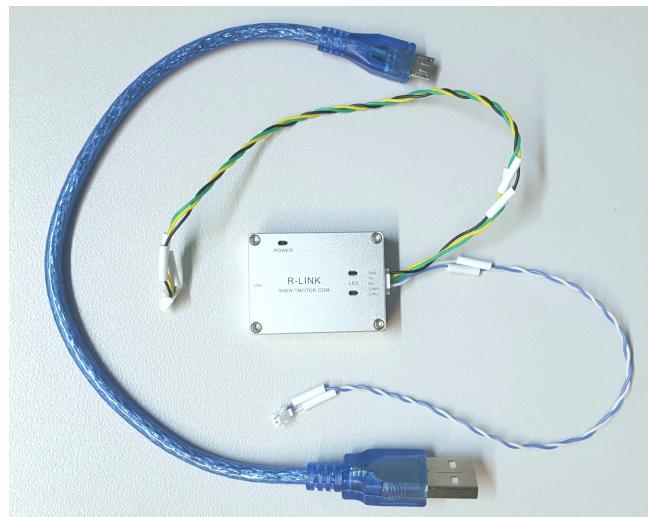
- **Silabs:** [CP210x Universal Windows Driver](#)
- **CH341:** [Sparkfun - How to install CH340 drivers](#)

6.1.1 Tutorials

- [T-MOTOR](#)
- [Skytentific](#)

6.1.2 UART Connection: R-Link module

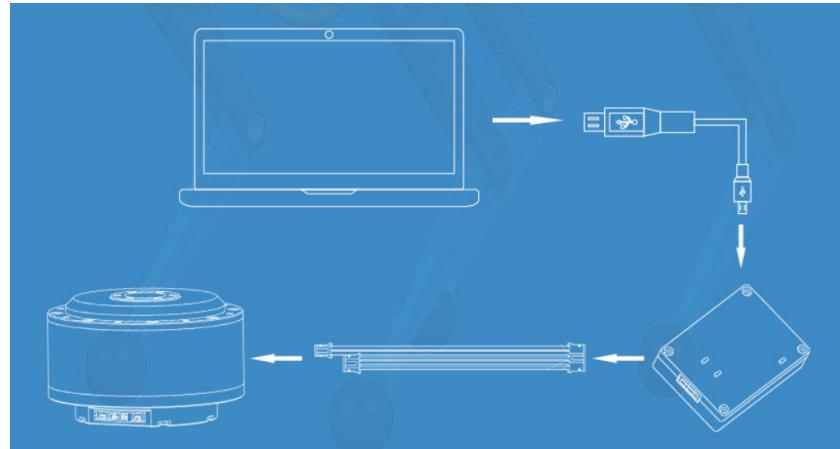
R-LINK is a USB to serial port module, specially designed for CubeMars A Series of dynamical modular motors. It is possible to calibrate the encoder in the module, change CAN ID settings, PID settings, as well as to control position, torque and speed of the motor within the configuration software tool.



6.1.3 Instructions: R-Link Config Tool

User manual & configuration tool: store-en.tmotor.com

1. Wire the R-LINK module as shown in the figure below. A USB to micro USB cable connects a pc with the R-LINK module and the 5pin cable goes between the R-LINK module and the Motor.



2. Connect the AK80-6 motor to a power supply (24V, 12A) and do not cut off the power before the setting is completed.

3. Start the R-Link Config Tool application (only runs on Windows).
4. Select serial port: USB-Serial_CH340, wch, cp along with an appropriate baud rate (both 921600 and 115200 Bd should work). If the serial port option USB-Serial_CH340,wch,cp does not show up, your pc can't establish a connection to the R-LINK module due to remaining driver issues.
5. Choose the desired motor settings on the left side of the config tool GUI. Enter the correct CAN ID of the motor under *MotorSelectEnter*. A label on the motor shows the ID.

- Velocity: 5 rad/s is a relatively slow speed of revolution, hence it offers a good starting point.
- Torque: be careful setting a fixed torque, because the friction inside the motor decreases with the speed of revolution. Therefore a fixed torque commonly leads to either no movement at all or accelerates the motor continuously.

4. Start the plotting by ticking the boxes of position, velocity, torque and select *Display*
5. Press *Run* to start recording the plots.
6. Enter *M_Mode* to control the motor. This is indicated by a color change of the plot line, from red to green.
7. In order to push changes in the settings to the motor, press *Send Once*.

Warning: This button does not work reliably. Usually it has to be activated several times before the setting changes actually apply on the motor.

8. Stop the motor inside the M-Mode by setting the velocity to 0 and pressing *Send Once* until the changes apply.
9. Exit *M_Mode* to exit the control mode of the motor.

Warning: The next time you start the motor control with *Enter M_Mode* the motor will restart with the exact same settings as you left the control mode with *Exit M_Mode*. This is especially dangerous if a weight is attached to the pendulum and the motor control was left with high velocity or torque settings.

10. Use *Stop* to deactivate the plotting.

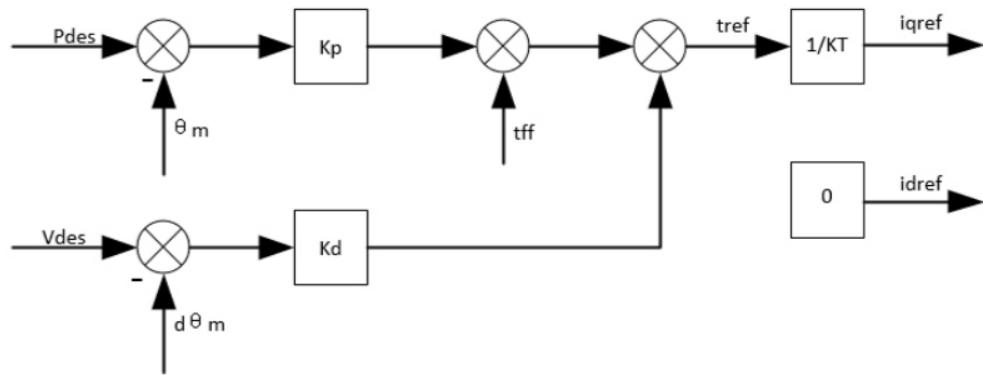
6.1.4 Debugging

Error messages that showed up during the configuration procedure, such as *UVLO* (VM undervoltage lockout) and *OTW* (Thermal warning and shutdown), could be interpreted with the help of the datasheet for the DRV8353M 100-V Three-Phase Smart Gate Driver from Texas Instruments:

Datasheet: [DRV8353M](#) (on the first Page under: 1. Features)

6.1.5 PD-Controller

A proportional-derivative controller, which is based on the MIT Mini-Cheetah Motor, is implemented on the motor controller board. The control block diagram of this closed loop controller is shown below. It can be seen that the control method is flexible, as pure position, speed, feedforward torque control or any combination of those is possible.



In the motor driver,:

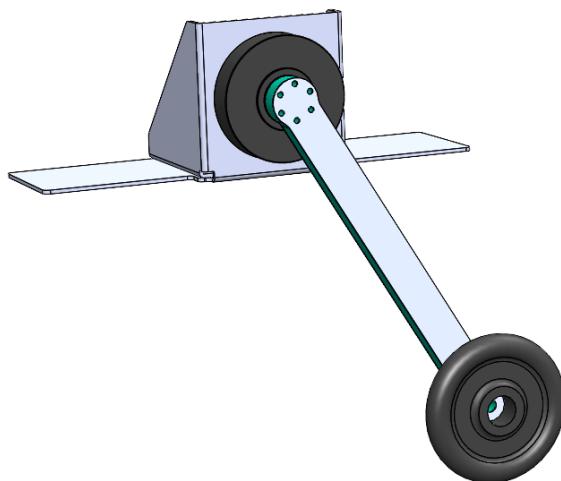
```
send_rad_command(position_in_radians, velocity_in_radians, Kp, Kd, tau_ff)
```

lets you set desired position (Pdes), velocity (Pvel), Kp, Kd and feedforward torque (tff) values at every time step.

6.2 Hardware & Testbench Description

The /hardware directory contains all information about the hardware that is used to built the simple pendulum test bench, including a bill of materials, step files of the CAD model along with wiring diagrams for the complete set up as well as the CAN bus.

We additionally uploaded all CAD files to grabcad.com. You can use the 3D viewer from their webiste to diplay the 3D model directly within your browser: grabcad.com/simple_pendulum



6.2.1 Physical Parameters of the Pendulum

- Point mass: $m_p = 0.546 \text{ Kg}$
- Mass of rod, mounting parts and screws: $m_r = 0.13 \text{ Kg}$
- Overall mass: $m = 0.676 \text{ Kg}$
- Length to point mass: $l = 0.5 \text{ m}$
- Length to COM: $l_{COM} = 0.45 \text{ m}$

$$l_{COM} = \frac{m_p l 0.5 m_r l}{m_p m_r}$$

6.2.2 Physical Parameters of the Actuator

The AK80-6 actuator from T-Motor is a quasi direct drive with a gear ratio of 6:1 and a peak torque of 12 Nm at the output shaft. The motor is equipped with an absolute 12 bit rotary encoder and an internal PD torque control loop. The motor controller is basically the same as the one used for MIT Mini-Cheetah, which is described [Ben Katz's MIT Mini-Cheetah Documentation](#)



- Voltage = 24 V
- Current = rated 12 A, peak 24 A
- Torque = rated 6 Nm, peak 12 Nm (after the transmission)
- Transmission N = 6 : 1
- Weight = 485 g
- Dimensions = Ø 98 mm x 38,5 mm
- Max. torque to weight ratio = 24 kg (after the transmission)
- Max. velocity = 38.2 s = 365 rpm (after the transmission)
- Backlash (accuracy) = 0.15° degrees

6.2.3 Motor Constants

Note: Before the transmission

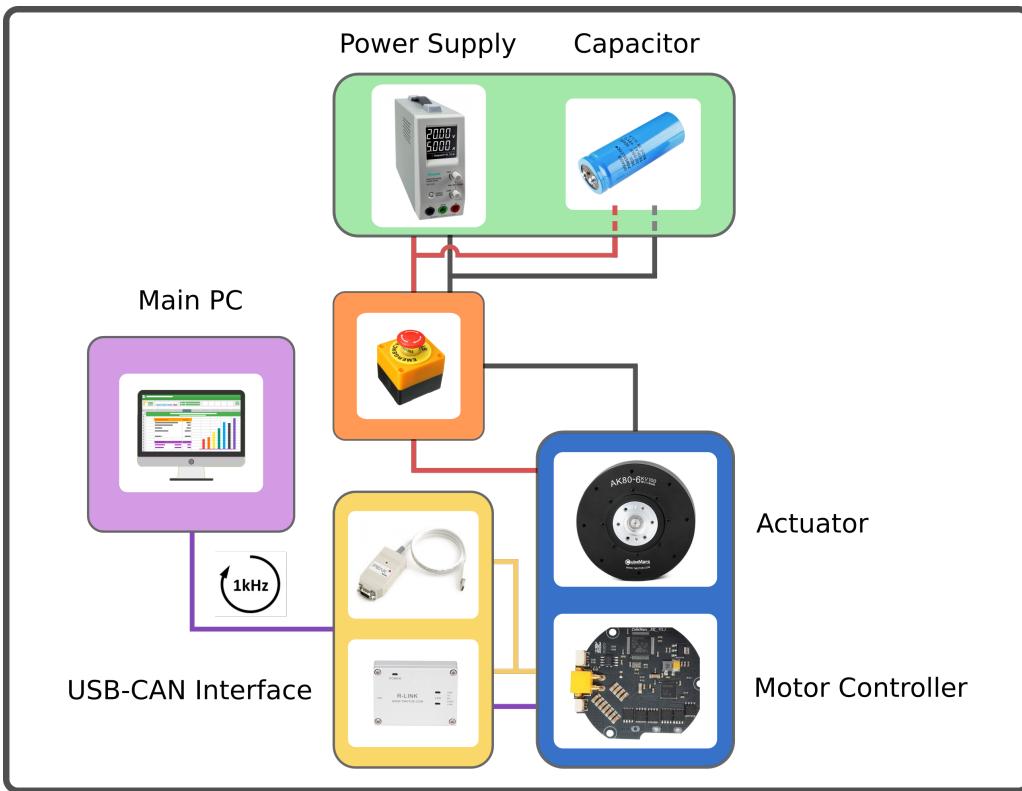
- Motor constant $km = 0.2206 \text{ Nm}/\sqrt{\text{W}}$
- Electric constant $ke = 0.009524 \text{ V}/\text{rpm}$
- Torque constant $kt = 0.091 \text{ Nm}/\text{A}$
- Torque = rated 1,092 Nm, peak 2,184 Nm
- Velocity / back-EMF constant $kv = 100 \text{ rpm}/\text{V}$
- Max. velocity at 24 V = $251.2 \text{ rad/s} = 2400 \text{ rpm}$
- Motor wiring in ∇ -delta configuration
- Number of pole pairs = 21
- Resistance phase to phase = $170 \pm 5 \text{ m}\Omega$
- Inductance phase to phase = $57 \text{ pm} 10 \mu\text{H}$
- Rotor inertia $I_r = 0.000060719 \text{ kg/m}^2$

6.2.4 Electrical Setup

Note: We do not give any safety warranties on the electrical wiring. All experiments and reproductions of our test bed are at your own risk.

The wiring diagram below shows how the simple pendulum testbench is set up. A main PC is connected to a motor controller board (**CubeMars_AK_V1.1**) mounted on the actuator (**AK80-6 from T-Motor**). The communication takes place on a CAN bus with a maximum signal frequency of 1Mbit/sec with the ‘classical’ CAN protocol. Furthermore, a USB to CAN interface is needed, if the main pc doesn’t have a PCI CAN card. Two different devices are used in our setup: the **R-LINK module** from T-Motor and the **PCAN-USB adapter from PEAK systems**. The former has CAN and UART connectors at the output, but only works with Windows. The latter only features CAN connection, but also works with Linux. The UART connector of the R-LINK module is usefull to configure and calibrate the AK80-6.

The actuator requires an input voltage of 24 Volts and consumes up to 24 Amps under full load. A power supply that is able to deliver both and which is used in our test setup is the **EA-PS 9032-40** from Elektro-Automatik. A capacitor filters the backEMF coming from the actuator and therefore protects the power supply from high voltage peaks. This wouldn’t be necessary if the actuator is powered from a battery pack, as in this case backEMF simply recharges the batteries. The capacitor we use is made of **10x single 2.7V-400 F capacitor cells** connected in series resulting a total capacity of 40 F and is wired in parallel to the motor. A emergency stop button serves as additional safety measure. It disconnects the actuator from power supply and capacitor, if only the power supply gets disconnected the actuator will keep running with the energy stored in the capacitor.



- Actuator: AK80-6
- Controller board: CubeMars_AK_V1.1
- Power supply: EA-PS 9032-40
- Capacitor: 10x 2.7V-400F cells connected in series
- USB-CAN interfaces: R-LINK module and PCAN-USB adapter.

6.2.5 backEMF

The reverse current resulting from switching motor speeds from high to low is called backEMF (Electro Magnetic Force). When the motor speed decreases the motor works as a generator, which converts mechanical energy into electrical energy and hence the additional current needs some path to flow. The energy recycled back into the input power supply causes a voltage spike and potential risk. It is necessary to add enough input capacitance to absorb this energy. A sufficiently large input capacitance is important in the design of the electric circuit. It is beneficial to have more bulk capacitance, but the disadvantages are increased cost and physical size.

If the power source were a perfect battery, then energy would flow back into the battery and be recycled. However, in our case the power source is a DC power supply. Especially power supplies with an inverse-polarity protection diode can only source current and cannot sink current, hence the only place the energy can go is into the bulk capacitor. The amount of energy stored in the bulk capacitor can be calculated with

$$E = \frac{1}{2} \cdot C \cdot (V_{max}^2 - V_{nom}^2)$$

where **C** is the capacitance and **V** is the voltage. In the case of a Simple Pendulum max. backEMF can be estimated from the kinetic energy of the pendulum

$$E_{kin} = \frac{1}{2}m \cdot v^2$$

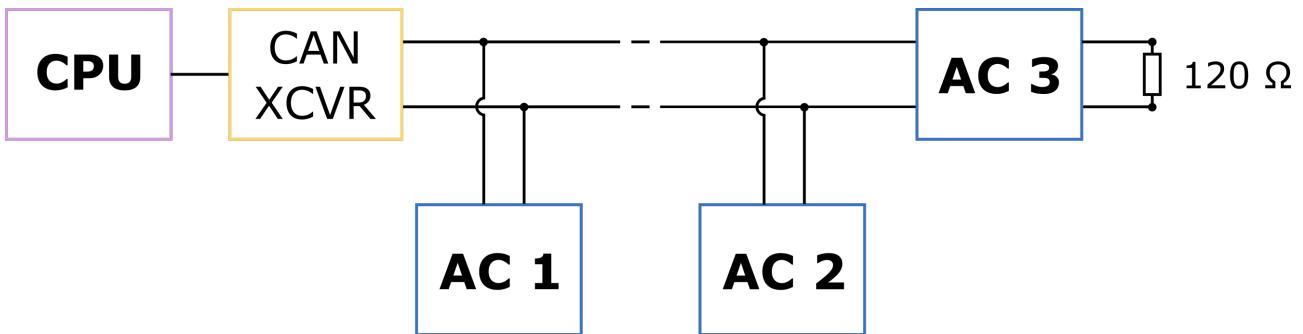
where **m** is the payload attached to the rod and **v** is the velocity of the payload. The voltage across the capacitor increases as energy flows into it, so the capacitor should be sized accordingly to the specific application requirements. Nevertheless tuning a capacitor to the acceptable min. capacity is tricky, because it depends on many factors including:

- External load
- Capacitance of the power supply to source current
- Motor braking method, output short brake or current polarity reversing brake.
- Amount of parasitic inductance between power supply and motor system, which limits the current change rate from the power supply. The larger the input capacitance, the more stable the motor voltage and higher current can be quickly supplied.
- The maximum supply voltage limit and acceptable voltage ripples

If the used capacitor is too small for your specific application it introduces the risk of burning the capacitor. The voltage rating for the bulk capacitors should be higher than the typical operating voltage and provide some safty margin. In our case we supply the AK80-6 with 24 V, whereas the capacitor can take up to 27 V. Therefore we have 3 V buffer, combined with a large capacity of 40 F, we ensure that during voltage spikes the capacitor never gets fully charged. If you don't want to buy a huge and expensive capacitor you may instead use a **break resistor**, which normally is cheaper to purchase. A guidance on this topic is provided [here](#). One drawback using brake resistors is that they quickly heat up, if the motor frequently brakes and regenerates energy. Another option to prevent the bus voltage from spiking too high are **resistive shunt regulators**, e.g. like this one from [polulu](#), but they can't dissipate much power and high-power versions also get expensive.

6.3 Communication: CAN Bus wiring

Along the CAN bus proper grounding and isolation is required. It is important to not connect ground pins on the CAN bus connectors between different actuators, since this would cause a critical ground loop. The ground pin should only be used to connect to systems with a ground isolated from the power ground. Additionally, isolation between the main pc and the actuators improves the signal quality. When daisy-chaining multiple actuators, only the CAN-High and CAN-Low pins between the drives must be connected. At the end of the chain a 120 Ohm resistor between CAN-H and CAN-L is used to absorb the signals. It prevents the signals from being reflected at the wire ends. The CAN protocol is differential, hence no additional ground reference is needed. The diagram below displays the wiring of the CAN bus.



- Main pc: CPU
- CAN transceiver: CAN XCVR
- Actuator: AC

CHAPTER SEVEN

TRAJECTORY OPTIMIZATION

7.1 Trajectory optimization using direct collocation

Note: Type: Trajectory Optimization

State/action space constraints: Yes

Optimal: Yes

Versatility: Swingup and stabilization

7.1.1 Theory

Direct collocation is an approach from **collocation methods**, which transforms the optimal control problem into a mathematical programming problem. The numerical solution can be achieved directly by solving the new problem using sequential quadratic programming [1] [2]. The formulation of the optimization problem at the collocation points is as follows:

$$\begin{aligned} \min_{\mathbf{x}[:, u[]]} & \sum_{n_0}^{N-1} h_{nl}(u[n]) \\ \text{s.t. } & \dot{\mathbf{x}}(t_{c,n}) = f(\mathbf{x}(t_{c,n}), u(t_{c,n})), \quad \forall n \in [0, N-1] \\ & |u| \leq u_{max} \\ & \mathbf{x}[0] = \mathbf{x}_0 \\ & \mathbf{x}[N] = \mathbf{x}_F \end{aligned}$$

- $\mathbf{x} = [\theta(.), \dot{\theta}(.)]^T$: Angular position and velocity are the states of the system
- u : Input torque of the system applied by motor
- $N = 21$: Number of break points in the trajectory
- $h_k = t_k - t_k$: Time interval between two breaking points
- $l(u) = u^T R u$: Running cost
- $R = 10$: Input weight

- $\dot{\mathbf{x}}(t_{c,n})$: Nonlinear dynamics of the pendulum considered as equality constraint at collocation point
- $t_{c,k} = \frac{1}{2}(t_k t_{k1})$: A collocation point at time instant k , (i.e., $\mathbf{x}[k] = \mathbf{x}(t_k)$), in which the collocation constraints depends on the decision variables $\mathbf{x}[k], \mathbf{x}[k2, B1], u[k], u[k2, B1]$
- $u_{max} = 10$: Maximum torque limit
- $\mathbf{x}_0 = [\theta = \mathbf{0}, \dot{\theta} = \mathbf{0}]$: Initial state constraint
- $\mathbf{x}_F = [\theta = \pi, \dot{\theta} = \mathbf{0}]$: Terminal state constraint

Minimum and a maximum spacing between sample times set to 0.05 and 0.5` s . It assumes a **first-order hold** on the input trajectory, in which the signal is reconstructed as a piecewise linear approximation to the original sampled signal.

7.1.2 API

The direct collocation algorithm explained above can be executed by using the `DirectCollocationCalculator` class:

```
dircal = DirectCollocationCalculator()
```

To parse the pendulum parameters to the calculator, do:

```
dircal.init_pendulum(mass=0.5,
                      length=0.5,
                      damping=0.1,
                      gravity=9.81,
                      torque_limit=1.5)
```

The optimal trajectory can be computed with:

```
x_trajectory, dircol, result = dircal.compute_trajectory(N=21,
                                                          max_dt=0.5,
                                                          start_state=[0.0, 0.0],
                                                          goal_state=[3.14, 0.0])
```

The method returns three pydrake objects containing the optimization results. The trajectory as numpy arrays can be extracted from these objects with:

```
T, X, XD, U = dircal.extract_trajectory(x_trajectory, dircol, result, N=1000)
```

where T is the time, X the position, XD the velocity and U the control trajectory. The parameter N determines here how with how many steps the trajectories are sampled.

The phase space of the trajectory can be plotted with:

```
dircal.plot_phase_space_trajectory(x_trajectory, save_to="None")
```

If a string with a path to a file location is parsed with ‘save_to’ the plot is saved there.

7.1.3 Dependencies

The trajectory optimization using direct collocation for the pendulum swing-up is accomplished by taking advantage of [Drake toolbox \[3\]](#).

7.1.4 References

- [1] Hargraves, Charles R., and Stephen W. Paris. “Direct trajectory optimization using nonlinear programming and collocation.” *Journal of guidance, control, and dynamics* 10.4 (1987): 338-342
- [2] Russ Tedrake. Underactuated Robotics: Algorithms for Walking, Running, Swimming, Flying, and Manipulation (Course Notes for MIT 6.832).
- [3] *Model-Based Design and Verification for Robotics* <<https://drake.mit.edu/>>

7.2 Iterative Linear Quadratic Regulator (iLQR)

Note: Type: Trajectory Optimization

State/action space contraints: No

Optimal: Yes

Versatility: Swingup and stabilization

7.2.1 Theory

The [iterative linear quadratic regularizer \(iLQR\) \[1\]](#) is an extension of the LQR controller. The LQR controller linearizes the dynamics at a given state and assumes that these linear dynamics are valid at every other system state as well. In contrast to that, the iLQR optimization method has the ability to take the full system dynamics into account and plan ahead by optimizing over a sequence of control inputs.

The algorithm can be described as:

1. Set an initial state x_0 and an initial control sequence $\mathbf{U} = [u_0, u_1, \dots, u_{N-1}]$, where N is the number of steps that will be optimized over (the time horizon).
2. Rollout the trajectory by applying the control sequence iteratively to the initial state.

The following steps are repeated until convergence:

3. Backward pass: Compute the derivatives of the cost function and the gains for the control sequence
4. Forward pass: Update the control sequence with the computed gains and rollout the new trajectory with the new control sequence. If the cost of the new trajectory is smaller than before, carry over the new control sequence and increase the gain factor. If not, keep the old trajectory and decrease the gain factor.

If the cost is below a specified threshold the algorithm stops.

7.2.2 API

The iLQR algorithm is computed in the iLQR_Calculator class. The class can be used as follows:

The iLQR calculator has to be initialized with the dimension of the state space (`n_x`) and the dimension of the actuation space (`n_u`) of the system:

```
iLQR = iLQR_Calculator(n_x=2, n_u=1)
```

For the pendulum `n_x=2` (positions and velocity) and `n_u=1`. Next the dynamics and cost function have to be set in the calculator by using:

```
iLQR.set_discrete_dynamics(dynamics)
iLQR.set_stage_cost(stage_cost)
iLQR.set_final_cost(final_cost)
```

where `dynamics` is a function of the form:

```
dynamics(x, u) :
    ...
    return xd
```

i.e. takes the current state and control input as inputs and returns the integrated dynamics. Note that the time step `dt` is set by the definition of this function.

Similarly, `stage_cost` and `final_cost` are functions of the form:

```
stage_cost(x, u) :
    ...
    return cost

final_cost(x) :
    ...
    return cost
```

Warning: These functions have to be differentiable either with the pydrake symbolic library or with sympy! Examples for these functions for the pendulum are implemented in `pendulum.py`. With the ‘partial’ function from the ‘functools’ package additional input parameters of these functions can be set before passing the function with the correct input parameters to the iLQR solver. For an example usage of the partial function for this context see `compute_pendulum_iLQR.py` in 1.80 - 1.87 for the dynamics and 1.93 - 1.113 for the cost functions.

Next: initialize the derivatives and the start state in the iLQR solver:

```
iLQR.init_derivatives()
iLQR.set_start(x0)
```

Finally, a trajectory can now be calculated with:

```
(x_trj, u_trj, cost_trace,
regu_trace, redu_ratio_trace, redu_trace) = iLQR.run_ilqr(N=1000,
                                                       init_u_trj=None,
                                                       init_x_trj=None,
                                                       max_iter=100,
                                                       regu_init=100,
                                                       break_cost_redu=1e-6)
```

The run_ilqr function has the inputs

- N: The number of timesteps to plan into the future
- init_u_trj: Initial guess for the control sequence (optional)
- init_x_trj: Initial guess for the state space trajectory (optional)
- max_iter: Maximum number of iterations of forward and backward passes to compute
- break_cost_redu: Break cost at which the computation stops early

Besides the state space trajectory `x_trj` and the control trajectory `u_trj` the calculation also returns the traces of the cost, regularization factor, the ratio of the cost reduction and the expected cost reduction and the cost reduction.

7.2.3 Usage

An example script for the pendulum can be found in the `examples` directory. It can be started with:

```
python compute_iLQR_swingup.py
```

7.2.4 Comments

The iLQR algorithm in this form cannot respect joint and torque limits. Instead, those have to be enforced by penalizing unwanted values in the cost function.

7.2.5 Requirements

Optional: `pydrake` [2] (see `getting_started`)

7.2.6 Notes

The calculations with the `pydrake` symbolic library are about 30% faster than the calculations based on the `sympy` library in these implementations.

7.2.7 References

[1] Y. Tassa, N. Mansard and E. Todorov, “Control-limited differential dynamic programming,” 2014 IEEE International Conference on Robotics and Automation (ICRA), 2014, pp. 1168-1175, doi: 10.1109/ICRA.2014.6907001.

[2] Model-Based Design and Verification for Robotics

7.3 Direct Optimal Control based on the FDDP algorithm

In this package, the single pendulum swing-up is performed using the direct optimal control based on the FDDP algorithm (C. Mastalli, 2019).

The script uses FDDP, BOXFddp can also be used with the same weights. BOXFddp allows to enforce the system’s torque limits.

The urdf model is modified to fit a pinocchio model.

7.3.1 Theory

The costs functions for the **Running model** is written as

$$l = \sum_{n=1}^{T-1} \alpha_n \Phi_n(q, \dot{q}, T)$$

With the following costs and weights, t_s denoting the final time horizon.

- **Torque minimization:** Minimization of the joint torques for realistic dynamic motions.

$$\Phi_1 = \| T(t) \|_2^2, \quad \alpha_1 = 1e-4$$

- **Posture regularization:** giving as input only the final reference posture.

$$\Phi_2 = \| q(t) - q^{ref}(t_{s-1}) \|_2^2, \quad \alpha_2 = 1e-5$$

- The costs functions for the **Terminal model** are applied to only one node (the terminal node) and is written as

$$l_T = \alpha_T \Phi_T(q, \dot{q})$$

With the following cost and weight, $T = t_{final}$ the final time horizon.

- **Posture regularization:** giving as input only the final reference posture.

$$\Phi_3 = \| q(T) - q^{ref}(T) \|_2^2, \quad \alpha_3 = 10^{10}$$

The weights α_i for this optimization problem are determined experimentally.

7.3.2 API

The BOXFDDP algorithm can be executed with the boxfddp_calculator class. It can be initialized with:

```
ddp = boxfddp_calculator(urdf_path=urdf_path,
                           enable_gui=True,
                           log_dir="log_data/ddp")
```

The urdf_path should point to the urdf of the pendulum in a format that pinocchio accepts. The urdf for a simple pendulum can be found in the data folder of this repository: [simplependul_dfki_pino_Mod.urdf](#). enable_gui can be set to True if the trajectory shall be visualized with pinocchio after computation. In the log_dir a urdf with modified pendulum parameters will be stored.

To set the correct pendulum parameters in the urdf with:

```
ddp.init_pendulum(mass=mass,
                   length=length,
                   inertia=inertia,
                   damping=damping,
                   coulomb_friction=coulomb_fric,
                   torque_limit=torque_limit)
```

After that the trajectory can be computed with:

```
T, TH, THD, U = ddp.compute_trajectory(start_state=np.array([0.0, 0.0]),
                                         goal_state=np.array([np.pi, 0.0]),
                                         weights=np.array([1] + [0.1]*1),
                                         dt=4e-2,
                                         T=150,
                                         running_cost_state=1e-5,
                                         running_cost_torque=1e-4,
                                         final_cost_state=1e10)
```

where weights contains the weights of the terminal and the running cost model. dt is the timestep length, T is the number of timesteps. running_cost_state, running_cost_torque and final_cost_state are the individual cost weights. The method returns the time trajectory T, the positiontrajectory TH, the velocity trajectory THD and the control trajectory U.

The trajectory can be plotted with:

```
ddp.plot_trajectory()
```

or simulated with gepetto with (for this enable_gui has to be set to True during the initialization):

```
ddp.simulate_trajectory_gepetto()
```

7.3.3 Usage

An example script for the pendulum can be found in the `examples` directory. It can be started with:

```
python compute_BOXFDDP_swingup.py
```

7.3.4 Dependencies

Crocoddyl

Pinocchio

For the display, Gepetto

7.3.5 References

- [1] Mastalli, Carlos, et al. “Crocoddyl: An efficient and versatile framework for multi-contact optimal control.” 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020. [arxiv link](#)

CHAPTER EIGHT

REINFORCEMENT LEARNING

8.1 Soft Actor Critic Training

Note: Type: Closed loop, learning based, model free

State/action space constraints: None

Optimal: Yes

Versatility: Swing-up and stabilization

8.1.1 Theory

The soft actor critic (SAC) algorithm is a reinforcement learning (RL) method. It belongs to the class of so called ‘model free’ methods, i.e. no knowledge about the system to be controlled is assumed. Instead, the controller is trained via interaction with the system, such that a (sub-)optimal mapping from state space to control command is learned. The learning process is guided by a reward function that encodes the task, similar to the usage of cost functions in optimal control.

SAC has two defining features. Firstly, the mapping from state space to control command is probabilistic. Secondly, the entropy of the control output is maximized along with the reward function during training. In theory, this leads to robust controllers and reduces the probability of ending up in suboptimal local minima.

For more information on SAC please refer to the original paper [1]:

8.1.2 API

The sac trainer can be initialized with:

```
trainer = sac_trainer(log_dir="log_data/sac_training")
```

During and after the training process the trainer will save logging data as well the best model in the directory provided via the `log_dir` parameter.

Before the training can be started the following three initialisations have to be made:

trainer.init_pendulum() trainer.init_environment() trainer.init_agent()

Warning: **Attention** Make sure to call these functions in this order as they build upon another.

The parameters of `init_pendulum` are:

- `mass`: mass of the pendulum
- `length`: length of the pendulum
- `inertia`: inertia of the pendulum
- `damping`: damping of the pendulum
- `coulomb_friction`: coulomb_friction of the pendulum
- `gravity`: gravity
- `torque_limit`: torque limit of the pendulum

The parameters of `init_environment` are:

- `dt`: timestep in seconds
- `integrator`: which integrator to use (`euler` or `runge_kutta`)
- `max_steps`: maximum number of timesteps the agent can take in one episode
- `reward_type`: Type of reward to use receive from the environment (continuous, discrete, `soft_binary`, `soft_binary_with_repellor` and `open_ai_gym`)
- `target`: the target state (`[np.pi, 0]` for swingup)
- `state_target_epsilon`: the region around the target which is considered as target
- `random_init`: How the pendulum is initialized in the beginning of each episode (`False`, `start_vicinity`, `everywhere`)
- `state_representation`: How to represent the state of the pendulum (should be 2 or 3). 2 for regular representation (position, velocity). 3 for trigonometric representation (`cos(position), sin(position), velocity`).

The parameters of `init_agent` are:

- `learning_rate`: learning_rate of the agent
- `warm_start`: whether to warm_start the agent
- `warm_start_path`: path to a model to load for warm starting
- `verbose`: Whether to print training information to the terminal

After these initialisations the training can be started with:

```
trainer.train(training_timesteps=1e6,  
             reward_threshold=1000,  
             eval_frequency=10000,
```

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```
n_eval_episodes=20,  
verbose=1)
```

where the parameters are:

- `training_timesteps`: Number of timesteps to train
- `reward_threshold`: Validation threshold to stop training early
- `eval_frequency`: evaluate the model every `eval_frequency` timesteps
- `n_eval_episodes`: number of evaluation episodes
- `verbose`: Whether to print training information to the terminal

When finished the `train` method will save the best model in the `log_dir` of the `trainer` object.

Warning: Attention: when training is started, the `log_dir` will be deleted. So if you want to keep a trained model, move the saved files somewhere else.

The training progress can be observed with tensorboard. Start a new terminal and start the tensorboard with the correct path, e.g.:

```
$> tensorboard --logdir log_data/sac_training/tb_logs
```

The default reward function used during training is `soft_binary_with_repellor`

$$r = \exp{-(\theta - \pi)^2 / (2 * 0.25^2)} - \exp{-(\theta - 0)^2 / (2 * 0.25^2)}$$

This encourages moving away from the stable fixed point of the system at $\theta = 0$ and spending most time at the target, the unstable fixed point $\theta = \pi$. Different reward functions can be used. Novel reward functions can be implemented by modifying the `swingup_reward` method of the training environment with an appropriate `if` clause, and then selecting this reward function in the `init_environment` parameters under the key '`reward_type`'. The training environment is located in `gym_environment`

8.1.3 Usage

For an example of how to train a sac model see the `train_sac.py` script in the examples folder.

The trained model can be used with the `sac controller`.

8.1.4 Comments

Todo: comments on training convergence stability

8.1.5 Requirements

- Stable Baselines 3 (<https://github.com/DLR-RM/stable-baselines3>)
- Numpy
- PyYaml

8.1.6 References

[1] [Haarnoja, Tuomas, et al. “Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor.” International conference on machine learning. PMLR, 2018.](<https://arxiv.org/abs/1801.01290>)

8.2 Deep Deterministic Policy Gradient Training

Note: Type: Closed loop, learning based, model free

State/action space constraints: None

Optimal: Yes

Versatility: Swing-up and stabilization

8.2.1 Theory

The Deep deterministic Policy Gradient (DDPG) algorithm is a reinforcement learning (RL) method. DDPG is a model-free off-policy algorithm. The controller is trained via interaction with the system, such that a (sub-)optimal mapping from state space to control command is learned. The learning process is guided by a reward function that encodes the task, similar to the usage of cost functions in optimal control.

DDPG can thought of Q-learning for continuous action spaces. It utilizes two networks, an actor and a critic. The actor receives a state and proposes an action. The critic assigns a value to a state action pair. The better an action suits a state the higher the value.

Further, DDPG makes use of target networks in order to stabilize the training. This means there are a training and a target version of the actor and critic models. The training version is used during training and the target networks are partially updated by polyak averaging:

$$\phi_{targ} = \tau \phi_{targ} + (1 - \tau) \phi_{train}$$

where τ is usually small.

DDPG also makes use of a replay buffer, which is a set of experiences which have been observed during training. The replay buffer should be large enough to contain a wide range of experiences. For more information on DDPG please refer to the original paper [1]:

This implementation losely follows the keras guide [2].

8.2.2 API

The ddpg trainer can be initialized with:

```
trainer = ddpg_trainer(batch_size=64,  
                      validate_every=20,  
                      validation_reps=10,  
                      train_every_steps=1)
```

where the parameters are

- `batch_size`: number of samples to train on in one training step
- `validate_every`: evaluate the training progress every `validate_every` episodes
- `validation_reps`: number of episodes used during the evaluation
- `train_every_steps`: frequency of training compared to taking steps in the environment

Before the training can be started the following three initialisations have to be made:

```
trainer.init_pendulum()  
trainer.init_environment()  
trainer.init_agent()
```

Warning: Attention: Make sure to call these functions in this order as they build upon another.

The parameters of `init_pendulum` are:

- `mass`: mass of the pendulum
- `length`: length of the pendulum
- `inertia`: inertia of the pendulum
- `damping`: damping of the pendulum
- `coulomb_friction`: coulomb_friction of the pendulum
- `gravity`: gravity
- `torque_limit`: torque limit of the pendulum

The parameters of `init_environment` are:

- `dt`: timestep in seconds
- `integrator`: which integrator to use (“euler” or “runge_kutta”)

- `max_steps`: maximum number of timesteps the agent can take in one episode
- `reward_type`: Type of reward to use receive from the environment (“continuous”, “discrete”, “soft_binary”, `soft_binary_with_repellor`” and “`open_ai_gym`”)
- `target`: the target state (`[np.pi, 0]` for swingup)
- `state_target_epsilon`: the region around the target which is considered as target
- `random_init`: How the pendulum is initialized in the beginning of each episode (“False”, “start_vicinity”, “everywhere”)
- `state_representation`: How to represent the state of the pendulum (should be 2 or 3). 2 for regular representation (position, velocity). 3 for trigonometric representation ($\cos(\text{position})$, $\sin(\text{position})$, velocity).
- `validation_limit`: Validation threshold to stop training early

The parameters of `init_agent` are:

- `replay_buffer_size`: The size of the `replay_buffer`
- `actor`: the tensorflow model to use as actor during training. If None, the default model is used
- `critic`: the tensorflow model to use as actor during training. If None, the default model is used
- `discount`: The discount factor to propagate the reward during one episode
- `actor_lr`: learning rate for the actor model
- `critic_lr`: learning rate for the critic model
- `tau`: determines how much of the training models is copied to the target models

After these initialisations the training can be started with:

```
trainer.train(n_episodes=1000,
              verbose=True)
```

where the parameters are:

- `n_episodes`: number of episodes to train
- `verbose`: Whether to print training information to the terminal

Afterwards the trained model can be saved with:

```
trainer.save("log_data/ddpg_training")
```

The save method will save the actor and critic model under the given path.

Warning: Attention: This will delete existing models at this location. So if you want to keep a trained model, move the saved files somewhere else.

The default reward function used during training is `open_ai_gym`

$$r = -(\theta - \pi)^2 - 0.1(\dot{\theta} - 0)^2 - 0.001u^2$$

This encourages spending most time at the target (in the equation ($[pi, 0]$) with actions as small as possible. Different reward functions can be used by changing the reward type in `init_environment`. Novel reward functions can be implemented by modifying the `swingup_reward` method of the training environment with an appropriate `if` clause, and then selecting this reward function in the `init_environment` parameters under the key '`reward_type`'. The training environment is located in `gym_environment`

8.2.3 Usage

For an example of how to train a sac model see the `train_ddpg.py` script in the examples folder.

The trained model can be used with the `ddpg` controller.

8.2.4 Comments

Todo: comments on training convergence stability

8.2.5 Requirements

- Tensorflow 2.x

8.2.6 References

[1] Lillicrap, Timothy P., et al. “Continuous control with deep reinforcement learning.” arXiv preprint arXiv:1509.02971 (2015).

[2] reras guide

TRAJECTORY-BASED CONTROLLERS

9.1 Open Loop Control

Note: Type: Open loop control

State/action space constraints: -

Optimal: -

Versatility: -

9.1.1 Theory

This controller is designed to feed a precomputed trajectory in from of a csv file to the simulator or the real pendulum. Particulary, the controller can process trajectories that have been found with help of the [trajectory optimization](#) methods.

9.1.2 API

The controller needs pendulum parameters as input during initialization:

```
OpenLoopController.__init__(self, data_dict)
    inputs:
        data_dict: dictionary
            A dictionary containing a trajectory in the below specified format
```

The `data_dict` dictionary should have the entries:

```
data_dict["des_time_list"] : desired timesteps
data_dict["des_pos_list"] : desired positions
data_dict["des_vel_list"] : desired velocities
data_dict["des_tau_list"] : desired torques
```

The values are assumed to be in SI units, i.e. time in s, position in rad, velocity in rad/s, torque in Nm.

The control output $\mathbf{u}(\mathbf{x})$ can be obtained with the API of the abstract controller class:

```
OpenLoopController.get_control_output(mean_pos, mean_vel, meas_tau, meas_time)
    inputs:
        meas_pos: float, position of the pendulum
        meas_vel: float, velocity of the pendulum
        meas_tau: not used
        meas_time: not used
    returns:
        des_pos, des_vel, u
```

The function returns the desired position, desired velocity and a torque as specified in the csv file at the given index. The index counter is incremented by 1 every time the `get_control_output` function is called.

9.1.3 Usage

Before using this controller, first a trajectory has to be defined/calculated and stored to csv file in a suitable format.

9.1.4 Comments

The controller will not scale the trajectory according to the time values in the csv file. All it does is return the rows of the file one by one with each call of `get_control_output`.

9.2 Proportional-Integral-Derivative (PID) Control

Note: Type: Closed loop control

State/action space constraints: -

Optimal: -

Versatility: -

9.2.1 Theory

This controller is designed to follow a precomputed trajectory from of a csv file to the simulator or the real pendulum. Particulary, the controller can process trajectories that have been found with help of the [trajectory optimization](#) methods.

The torque processed by the PID control terms via (with feed forward torque):

$$u(t) = \tau K_p e(t) K_i \int_0^t e(t') dt' + K_d \frac{de(t)}{dt}$$

where τ is the torque from the csv file and $e(t)$ is the position error at timestep t . Without feed forward torque, the torque from the precomputed trajectory file is omitted:

$$u(t) = K_p e(t) K_i \int_0^t e(t') dt' K_d \frac{de(t)}{dt}$$

9.2.2 API

The controller needs pendulum parameters as input during initialization:

```
PIDController.__init__(self, data_dict, Kp, Ki, Kd, use_feed_forward=True)
    inputs:
        data_dict: dictionary
            A dictionary containing a trajectory in the below specified format
        Kp : float
            proportional term,
            gain proportional to the position error
        Ki : float
            integral term,
            gain proportional to the integral
            of the position error
        Kd : float
            derivative term,
            gain proportional to the derivative of the position error
        use_feed_forward : bool
            whether to use the torque that is provided in the csv file
```

The `data_dict` dictionary should have the entries:

```
data_dict["des_time_list"] : desired timesteps
data_dict["des_pos_list"] : desired positions
data_dict["des_vel_list"] : desired velocities
data_dict["des_tau_list"] : desired torques
```

The values are assumed to be in SI units, i.e. time in s, position in rad, velocity in rad/s, torque in Nm.

The control output $\mathbf{u}(\mathbf{x})$ can be obtained with the API of the abstract controller class:

```
PIDController.get_control_output(mean_pos, mean_vel, meas_tau, meas_time)
    inputs:
        meas_pos: float, position of the pendulum
        meas_vel: float, velocity of the pendulum
        meas_tau: not used
        meas_time: not used
    returns:
        des_pos, des_vel, u
```

The function returns the desired position, desired velocity as specified in the csv file at the given index. The returned torque is processed by the PID controller as described in the theory section.

The index counter is incremented by 1 every time the `get_control_output` function is called.

9.2.3 Usage

Before using this controller, first a trajectory has to be defined/calculated and stored to csv file in a suitable format.

9.2.4 Comments

The controller will not scale the trajectory according to the time values in the csv file. All it does is process the rows of the file one by one with each call of `get_control_output`.

9.3 Time-varying Linear Quadratic Regulator (TVLQR)

Note: Type: Closed loop control

State/action space constraints: -

Optimal: -

Versatility: -

9.3.1 Theory

This controller is designed to follow a precomputed trajectory from of a csv file to the simulator or the real pendulum. Particulary, the controller can process trajectories that have been found with help of the [trajectory optimization](#) methods.

The Time-varying Linear Quadratic Regulator (TVLQR) is an extension to the regular [LQR controller](#). The LQR formalization is used for a time-varying linear dynamics function

$$\dot{\mathbf{x}} = \mathbf{A}(t)\mathbf{x}\mathbf{B}(t)\mathbf{u}$$

The TVLQR controller tries to stabilize the system along a nominal trajectory. For this, at every timestep the system dynamics are linearized around the state of the nominal trajectory $\mathbf{x}_0(t)$, $\mathbf{u}_0(t)$ at the given timestep t . The LQR formalism then can be used to derive the optimal controller at timestep t :

$$u(\mathbf{x}) = \mathbf{u}_0(t) - \mathbf{K}(t)(\mathbf{x} - \mathbf{x}_0(t))$$

For further reading, we recommend chapter 8 of this [Underactuated Robotics \[1\]](#) lecture.

9.3.2 API

The controller needs pendulum parameters as input during initialization:

```
TVLQRController.__init__(self, data_dict, mass, length, damping, gravity,_
                        torque_limit)
    inputs:
        data_dict: dictionary
            A dictionary containing a trajectory in the below specified format
        mass: float, default: 1.0
        length: float, default: 0.5
        damping: float, default: 0.1
        gravity: float, default: 9.81
        torque_limit: float, default: np.inf
```

The data_dict dictionary should have the entries:

```
data_dict["des_time_list"] : desired timesteps
data_dict["des_pos_list"] : desired positions
data_dict["des_vel_list"] : desired velocities
data_dict["des_tau_list"] : desired torques
```

The values are assumed to be in SI units, i.e. time in s, position in rad, velocity in rad/s, torque in Nm.

The control output **u(x)** can be obtained with the API of the abstract controller class:

```
TVLQRController.get_control_output(mean_pos, mean_vel, meas_tau, meas_time)
    inputs:
        meas_pos: float, position of the pendulum
        meas_vel: float, velocity of the pendulum
        meas_tau: not used
        meas_time: not used
    returns:
        des_pos, des_vel, u
```

The function returns the desired position, desired velocity as specified in the csv file at the given index. The returned torque is processed by the TVLQR controller as described in the theory section.

The index counter is incremented by 1 every time the get_control_output function is called.

9.3.3 Usage

Before using this controller, first a trajectory has to be defined/calculated and stored to csv file or dictionary in a suitable format.

9.3.4 Dependencies

The trajectory optimization using direct collocation for the pendulum swing-up is accomplished by taking advantage of [Drake toolbox \[2\]](#).

9.3.5 Comments

The controller will not scale the trajectory according to the time values in the csv file. All it does is process the rows of the file one by one with each call of `get_control_output`.

9.3.6 References

- [1] Russ Tedrake. Underactuated Robotics: Algorithms for Walking, Running, Swimming, Flying, and Manipulation (Course Notes for MIT 6.832).
- [2] Model-Based Design and Verification for Robotics.

9.3.7 Region of Attraction (RoA) estimation

The region of attraction estimation is an offline process that can be applied to the closed-loop dynamics of a system (Plant and Controller) in order to analyze the control behaviour. The time-varying version of this analysis offers a very interesting point of view to understand how much the state can vary with respect to a nominal trajectory that brings a fixed initial state to a desired state. Hence, this process results in a very powerful tool to verify the robustness of a time-varying controller.

Probabilistic method

For simple systems, such as the torque limited simple pendulum under TVLQR control, the RoA can be estimated by a very intuitive simulation-based method. The implemented solution takes inspiration from some related works that has been studied and extended. E. Najafi proposed a computationally effective sampling approach to estimate the DoAs of nonlinear systems in real time:

E. Najafi, R. Babuška, and G. A. D. Lopes, “A fast sampling method for estimating the domain of attraction,” *Nonlinear Dyn*, vol. 86, no. 2, pp. 823–834, Oct. 2016, doi: 10.1007/11071-016-2926-7.

He used this method for estimating a time-invariant region of attraction in two different ways: “memoryless sampling” and “sampling with memory”. We have exploited his results from the memoryless version by extending the study to the time-varying case. This extension has been already somehow addressed by P. Reist which included it in a simulation-based variant of the LQR-Tree feedback-motion-planning approach:

P. Reist, P. V. Preiswerk, and R. Tedrake, “Feedback-motion-planning with simulation-based lqr-trees”, SAGE, 2016, https://groups.csail.mit.edu/robotics-center/public_papers/Reist15.pdf.

However, his implementation is strictly related to the LQR-Tree algorithm while we will focus on the region of attraction estimation.

Estimation procedure

First we have to fix the number of knot points N . Except for the given last value, ρ is initially fixed to an N -dimensional array of infinity. The last value of ρ comes from the time-invariant region of attraction estimation, while the other ones have to be fixed big enough to overcome its “real” value. Now, after computing the nominal trajectory and the related TVLQR controller that bring to the goal the estimation process can start. Iterating backward in the knot points, we can exploit the knowledge of the final ρ from the time-invariant case. The “previous” and the “next” ellipse have been considered. We sample random initial states from the “previous” ellipse and we simulate them until the “next” one. In doing so, we can check if the simulated trajectory exits from the “next” ellipse. The condition is the following one:

$$x^T S x < \rho$$

If a simulated trajectory triggers this condition, the algorithm shrinks the “previous” ellipse using the value of the computed optimal cost to go:

$$\rho_{new} = \min(\rho_{old}, ctg)$$

An implementation detail gives the possibility to reduce the time consumption. The estimation of each ellipse has been considered done after a maximum number of successful simulations.

SOS method

For the class of systems with polynomial dynamics $f(x)$, this problem can be formulated as a convex optimization problem using sums-of-squares (SOS) optimization. This different approach has very interesting advantages in terms of Scalability and it doesn't need any Discretization in the time domain. Furthermore, it allows to reason about the RoA algebraically and does not require numerical simulations, that can be expensive. On the other hand, it requires to express the closed-loop dynamics in a polynomial form. This might need some approximation, via Taylor series for examples, of the dynamics that can cause some difference between the simulation and the real behaviour.

My implementation of this estimation method is based on:

- Invariant Funnels around Trajectories using Sum-of-Squares Programming”, Mark M. Tobenkin, Ian R. Manchester, Russ Tedrake (<https://doi.org/10.3182/20110828-6-IT-1002.03098>)
- Funnel libraries for real-time robust feedback motion planning”, Anirudha Majumdar, Russ Tedrake (<https://doi.org/10.1177/0278364917712421>)
- Trajectory Optimization and Time-Varying LQR Stabilization of Airplane Longitudinal Dynamics” (<https://github.com/benthomsen/mit-6832-project/blob/master/bthomsen-6832-report.pdf>)

Estimation procedure

$$\begin{aligned} \max_{\rho_i, \lambda_i} \quad & \rho_i \\ \text{subject to} \quad & -(\dot{V} - \dot{\rho}_i) + \lambda_i(V - \rho_i) \text{ is SOS} \\ & \lambda_i \text{ is SOS} \\ & \rho_i > 0 \end{aligned}$$

This is the optimization problem that has to be solved in order to obtain the value of rho. The Lyapunov condition has been imposed by exploiting the so-called S-procedure. Unfortunately, this formulation is not convex in rho, so that it has to be solved with a bilinear alternation by fixing at each step the Lagrangian multiplier or rho.

Furthermore, it is worthwhile to mention the consequences of considering the input saturation constraint. It can be addressed by using some Lagrangian multipliers. However, this can lead to add a number of SOS conditions that grows exponentially with the number of inputs. Hence, this has to be considered in systems where there is a big number of inputs.

9.4 iLQR Model Predictive Control

Note: Type: Model Predictive Control

State/action space contraints: No

Optimal: Yes

Versatility: Swingup and stabilization

9.4.1 Theory

This controller uses the trajectory optimization from the iLQR algorithm (see [iLQR](#)) in an MPC setting. This means that this controller recomputes an optimal trajectory (including the optimal sequence of control inputs) at every time step. The first control input of this solution is returned as control input for the current state. As the optimization happens every timestep the iLQR algorithm is only executed with one forward and one backward pass. As initial trajectory the solution of the previous timestep is parsed to the iLQR solver.

9.4.2 Requirements

pydrake (see [getting_started](#))

9.4.3 API

The controller can be initialized as:

```
controller = iLQRMPCCController(mass=0.5,
                                  length=0.5,
                                  damping=0.1,
                                  coulomb_friction=0.0,
                                  gravity=9.81,
                                  x0=[0.0, 0.0],
                                  dt=0.02,
                                  N=50,
                                  max_iter=1,
                                  break_cost_redu=1e-1,
                                  sCu=30.0,
                                  sCp=0.001,
                                  sCv=0.001,
                                  sCen=0.0,
                                  fCp=100.0,
                                  fCv=1.0,
                                  fCen=100.0,
                                  dynamics="runge_kutta",
                                  n_x=n2)
```

where

- mass, length, damping, coulomb_friction, gravity are the pendulum parameters (see [PendulumPlant](#))
- x0: array like, start state
- dt: float, time step
- N: int, time steps the controller plans ahead
- max_iter: int, number of optimization loops
- break_cost_redu: cost at which the optimization stops
- sCu: float, stage cost coefficient penalizing the control input every step
- sCp: float, stage cost coefficient penalizing the position error every step
- sCv: float, stage cost coefficient penalizing the velocity error every step
- sCen: float, stage cost coefficient penalizing the energy error every step
- fCp: float, final cost coefficient penalizing the position error at the final state
- fCv: float, final cost coefficient penalizing the velocity error at the final state
- fCen: float, final cost coefficient penalizing the energy error at the final state

- `dynamics`: string, “euler” for euler integrator, “runge_kutta” for Runge-Kutta integrator
- `nx`: int, `nx=2`, or `n_x=3` for pendulum, `n_x=2` uses $[\theta, \dot{\theta}]$ as pendulum state during the optimization, `n_x=3` uses $[\cos(\theta), \sin(\theta), \dot{\theta}]$ as state

Before using the controller a goal has to be set via:

```
controller.set_goal(goal=[np.pi, 0])
```

which initializes the cost function derivatives inside the controller for the specified goal.

It is possible to either load an initial guess for the trajectory from a csv file by using:

```
controller.load_initial_guess(filepath="../../../../data/trajectories/iLQR/
➥trajectory.csv")
```

for example a trajectory that has been found with the offline trajectory optimization iLQR. Alternatively, it is possible to compute a new initial guess with:

```
controller.compute_initial_guess(N=50)
```

With an initial guess set the control output can be obtained with the standard controller api:

```
controller.get_control_output(meas_pos, meas_vel,
➥meas_tau=0, meas_time=0):
```

where only the measured position (`meas_pos`) and measured velocity (`meas_vel`) are used in the control loop. The function returns

- None, None, `u`

`get_control_output` returns None for the desired position and desired velocity (the iLQR controller is a pure torque controller). `u` is the first control input of the computed control sequence. as described in the Theory section.

9.4.4 Usage

The controller can be tested in simulation with:

```
python sim_ilqrMPC.py
```

9.4.5 Comments

For `coulomb_fricitons != 0` the optimization gets considerably slower.

POLICY-BASED CONTROLLERS

10.1 Gravity Compensation Control

Note: Type: Closed loop control

State/action space constraints: -

Optimal: -

Versatility: only compensates for gravitational force acting on the pendulum, no swing-up or stabilization at the upright position

10.1.1 Theory

A controller compensating the gravitational force acting on the pendulum. The control function is given by:

$$u(\theta) = mgl \sin(\theta)$$

where u is commanded torque, m is a weight of $0,5\text{ kg}$ attached to the rod together with the mass of the rod and the mounting parts, l is the length of $0,5\text{ m}$ of the rod, g is gravitational acceleration on earth of $9,81\text{ ms}^{-2}$ and θ is the current position of the pendulum.

While the controller is running it actively compensates for the gravitational force acting on the pendulum, therefore the pendulum can be moved as if it was in zero-g.

10.2 Energy Shaping Control

Note: Type: Closed loop control

State/action space constraints: No

Optimal: No

Versatility: Swingup only, additional stabilization needed at the upright unstable fixed point via LQR controller

10.2.1 Theory

The energy of a simple pendulum in state $x = [\theta, \dot{\theta}]$ is given by:

$$E(\theta, \dot{\theta}) = \frac{1}{2}ml^2\dot{\theta}^2 - mgl \cos(\theta)$$

where the first term is the kinetic energy of the system and the second term is the potential energy. In the standing upright position $[pi, 0]$ the whole energy of the pendulum is potential energy and the kinetic energy is zero. As that is the goal state of a swingup motion, the desired energy can be defined as the energy of that state:

$$E_{des} = mgl$$

The idea behind energy-shaping control is simple:

- If $E < E_{des}$, the controller adds energy to the system by outputting torque in the direction of motion.
- If $E > E_{des}$, the controller subtracts energy from the system by outputting torque in the opposite direction of the direction of motion.

Consequently, the control function reads:

$$u(\theta, \dot{\theta}) = -k\dot{\theta} (E(\theta, \dot{\theta}) - E_{des}), \quad k \geq 0$$

This controller is applicable in the whole state space of the pendulum, i.e. it will always push the system towards the upright position. Note however, that the controller does not stabilize the upright position! If the pendulum overshoots the unstable fixpoint, the controller will make the pendulum turn another round.

In order to stabilize the pendulum at the unstable fixpoint, energy-shaping control can be combined with a stabilizing controller such as the LQR controller.

10.2.2 API

The controller needs pendulum parameters as well as the control term k (see equation (3)) as input during initialization:

```
EnergyShapingController.__init__(self, mass=1.0, length=0.5, damping=0.1,_
                                gravity=9.81, k=1.0)
    inputs:
        mass: float, default: 1.0
        length: float, default: 0.5
        damping: float, default: 0.1
        gravity: float, default: 9.81
        k: float, default: 1.0
```

Before using the controller, the function `EnergyShapingController.set_goal` must be called with input:

```
EnergyShapingController.set_goal(x)
    inputs:
        x: list of length 2
```

where \mathbf{x} is the desired goal state. This function sets the desired energy for the output calculation.

The control output $\mathbf{u}(\mathbf{x})$ can be obtained with the API of the abstract controller class:

```
EnergyShapingController.get_control_output(mean_pos, mean_vel, meas_tau, meas_
→time)
inputs:
    meas_pos: float, position of the pendulum
    meas_vel: float, velocity of the pendulum
    meas_tau: not used
    meas_time: not used
returns:
    None, None, u
```

`get_control_output` returns `None` for the desired position and desired velocity (the energy shaping controller is a pure torque controller). The returned torque u is the result of equation (3).

10.2.3 Usage

A usage example can be found in the [examples folder](#). Start a simulation with energy-shaping control for pendulum swingup and lqr control stabilization at the unstable fixpoint:

```
python sim_energy_shaping.py
```

10.3 LQR Control

Note: Type: Closed loop control

State/action space constraints: No

Optimal: Yes

Versatility: Stabilization only

10.3.1 Theory

A linear quadratic regulator (LQR) can be used to stabilize the pendulum at the unstable fixpoint. For a linear system of the form

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$

and a infinite horizon cost function in quadratic form:

$$J = \int_0^{\infty} (\mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{u}^T \mathbf{R} \mathbf{u}) dt, \quad \mathbf{Q} = \mathbf{Q}^T \succeq 0, \mathbf{R} = \mathbf{R}^T \succeq 0$$

the (provably) optimal controller is

$$u(\mathbf{x}) = -\mathbf{R}^{-1}\mathbf{B}^T\mathbf{S}\mathbf{x} = -\mathbf{Kx}$$

where \mathbf{S} has to fulfill the algebraic Riccati equation

$$\mathbf{SA} + \mathbf{A}^T\mathbf{S} - \mathbf{SBR}^{-1}\mathbf{BS} + \mathbf{Q} = 0$$

There are many solvers for the algebraic Riccati equation. In this library the solver from the `scipy` package is used.

10.3.2 API

The controller needs pendulum parameters as input during initialization:

```
LQRController.__init__(self, mass=1.0, length=0.5, damping=0.1, gravity=9.81,  

→torque_limit=np.inf)  

inputs:  

    mass: float, default: 1.0  

    length: float, default: 0.5  

    damping: float, default: 0.1  

    gravity: float, default: 9.81  

    torque_limit: float, default: np.inf
```

The control output $\mathbf{u}(\mathbf{x})$ can be obtained with the API of the abstract controller class:

```
LQRController.get_control_output(mean_pos, mean_vel, meas_tau, meas_time)  

inputs:  

    meas_pos: float, position of the pendulum  

    meas_vel: float, velocity of the pendulum  

    meas_tau: not used  

    meas_time: not used  

returns:  

    None, None, u
```

`get_control_output` returns `None` for the desired position and desired velocity (the LQR controller is a pure torque controller). The returned torque u is the result of equation (3). If the calculated torque is out of bounds of the pendulum's torque limits the controller will return $u=None$ as torque.

10.3.3 Usage

A usage example can be found in the `examples` folder. The controller can be tested in simulation with:

```
python sim_lqr.py
```

10.3.4 Comments

Without torque limits the LQR controller can drive the pendulum up from any position in a straight way. In practice this controller should only be used for stabilizing the pendulum at the unstable fixpoint. If the controller would require a torque larger than the pendulums torque limit, the controller returns None instead. This makes it possible to combine this controller with another controller and only use the LQR control if the output is not None. The region of attraction where this controller is able to stabilize the pendulum depends on the pendulum parameters and especially its torque limits.

10.3.5 Region of Attraction (RoA) estimation

The RoA estimation is a process that can be applied to the closed-loop dynamics of a system, i.e. Plant + Controller, in order to analize its state-space behaviour. Two different methods have been implemented here for studying the dynamics of the underactuated pendulum coupled with an LQR controller.

SOS method

The implementation here is based on

Tedrake, Russ, Ian R. Manchester, Mark Tobenkin, and John W. Roberts. “LQR-Trees: Feedback Motion Planning via Sums-of-Squares Verification.” *The International Journal of Robotics Research* 29, no. 8 (July 2010): 1038–52. <https://doi.org/10.1177/0278364910369189>.

Sum of squares optimization provides a natural generalization of SDP to optimizing over positive polynomials. Hence this method can be exploited to formulate and solve problems from Lyapunov analysis, at least for the polynomial systems. Furthermore, any sublevel set of a Lyapunov function is also an invariant set. This permitts to use sublevel sets of a Lyapunov function as approximation of the region of attraction for nonlinear systems.

First, the simple pendulum plant has been put in polynomial form via Taylor approximation around the up-right position, which will be the goal of the LQR controller. From different tests it seems that at least the third order approximation is necessary to obtain a satisfying result.

The LQR controller has been initialized to stabilize our closed-loop system around the up-right position. From that it has been obtained a state feedback matrix K and a matrix S, which is the solution of the matrix Lyapunov equation. The last one is very usefull because it can be used to obtain the Lyapunov function as $x^T S x$. After obtaining the Lyapunov function the feasibility problem can be formulated as

$$-\dot{V}(x) + \lambda(x)(V(x) - \rho) \text{ is SOS} \quad \text{and} \quad \lambda(x) \text{ is SOS}$$

This is coming from the so called “S-procedure” which makes use of the concept of Lagrangian multiplier to fomulate the Lyapunov conditions. It is important to highlight that other contraints are needed to include the torque inputs limits in the optimization problem.

Eventually, the above problem only verify one-sublevel set of the Lyapunov function. In order to obtain the best estimation, searching for the largest rho that can satisfy these conditions is necessary. The two different methods that have been implemented are described below.

Maximization of ρ : Simple line search

Since the problem is convex with rho fixed, and ρ is just a scalar, a simple line search on ρ can be performed to find the maximum for which the convex optimization returns a feasible solution. In particular, a bisection-like algorithm has been implemented here for such a purpose. However, since this formulation can be computationally heavy then other formulations might be considered.

Maximization of ρ : Equality-constrained formulation

This is an important variation since it makes use of the “S-procedure” to make the problem be jointly convex in $\lambda(x)$ and ρ , so a single convex optimization is needed. Under the assumption that $\dot{V}(x)$ is negative-definite at the fixed point, the problem can be written as

$$\begin{aligned} \max_{\rho, \lambda} \quad & \rho \\ & (x^T x)^d (V(x) - \rho) + \lambda(x) \dot{V}(x) \quad \text{is SOS} \end{aligned}$$

Also in this case, input limits have then to be included to obtain the desired result.

Probabilistic Method

For simple systems, such as the torque limited simple pendulum under LQR control, the RoA can be estimated by just evaluating the Lyapunov conditions for initial states from a continuously shrinking estimate of the ROA. This approach was introduced in:

- E. Najafi, R. Babuška, and G. A. D. Lopes, “A fast sampling method for estimating the domain of attraction,” Nonlinear Dyn, vol. 86, no. 2, pp. 823–834, Oct. 2016, doi: 10.1007/s11071-016-2926-7.

The RoA is estimated by a sublevel set of a quadratic Lyapunov function:

$$\mathcal{B} = \{\mathbf{x} | V(\mathbf{x}) < \rho\} = \{\mathbf{x} | V(\bar{\mathbf{x}}^T \mathbf{S} \bar{\mathbf{x}}) < \rho\}.$$

Where $\mathbf{x} = \mathbf{x} - \mathbf{x}^*$ denotes the deviation from the fixed point \mathbf{x}^*

A random initial condition $V(\hat{\mathbf{x}})$ is sampled from \mathcal{B} and the Lyapunov conditions ($V(\hat{\mathbf{x}}) > 0$ and $\dot{V}(\hat{\mathbf{x}}) = \nabla V \mathbf{f}(\hat{\mathbf{x}}) < 0$) are evaluated. If these conditions are satisfied, the next initial state is sampled. However, if these conditions are not met, the estimate is shrunk, such that $\rho = V(\hat{\mathbf{x}})$

Comments

Further possible improvements:

- Verifying the dynamics in implicit form will be necessary for more complex systems where the mass is not a scalar value. The SOS framework premitts it and would be usefull to try.
- Implementing more efficient ways to come up with a polynomial representation of the closed-loop dynamics. Approxiations usually generate differences between the real behaviour and the simulated one.
- Quotient ring of algebraic varieties in the “Equality-constrained formulation”.

CONTROLLER ANALYSIS

11.1 Controller Benchmarking

The controller benchmarking class can benchmark the controllers in simulation with respect to a predefined properties.

11.1.1 Definitions

The controller benchmark currently computes the following properties

- **Controller Frequency:** How fast can the controller process a pendulum state and return a control output. Measured in calls per second (Hz).
- **Swingup time:** How long does it take for the controller to swing-up the pendulum from the lower fixpoint to the upper fixpoint. Units: Seconds (s)
- **Energy consumption:** How much energy does the controller use during the swingup motion and holding the pendulum stable afterwards. Energy usage is measured by comparing the energy level of the actuated pendulum with a free falling pendulum. Units: Joule (J).
- **Smoothness** measures how much the controller changes the control output during execution. The calculated value is the standard deviation of the differences of all consecutive control signals.
- **Consistency** measures if the controller is able to drive the pendulum to the unstable fixpoint for varying starting positions and velocities. The start position is randomly chosen between $[-\pi, \pi]$ and the velocity is drawn from the intervall $[-3\pi/s, 3\pi/s]$.
- **Robustness** tests the controller abilities to recover from perturbations during the swingup motions. The controller is perturbed four times for 1 entire second with a random amount of torque.
- **Sensitivity:** Here the pendulum parameters (mass, length, friction) are modified without using this knowledge in the controller. This tests how sensitive the controller is to the model parameters.
- **Reduced torque limit:** This test checks a list of torque limits to find the minimal torque limit with which the controller is still able to swing-up the pendulum.

11.1.2 API

To initialize the benchmark class do:

```
from simple_pendulum.analysis.benchmark import benchmarker

ben = benchmarker(dt=dt,
                  max_time=max_time,
                  integrator=integrator,
                  benchmark_iterations=benchmark_iterations)
```

where dt is the control frequency, max_time the time of a single motion, integrator the integrator to be used (“euler” or “runge_kutta”, see [simulator](#)) and benchmark_iterations is the number iterations that are used to do the benchmark test.

The parameters of the pendulum can be parsed to the benchmark class with:

```
ben.init_pendulum(mass=mass,
                   length=length,
                   inertia=inertia,
                   damping=damping,
                   coulomb_friction=coulomb_fric,
                   gravity=gravity,
                   torque_limit=torque_limit)
```

The controller to be tested has to be set by:

```
ben.set_controller(controller)
```

where controller is a controller inheriting from the [abstract controller class](#).

The benchmark calculations are then started with:

```
ben.benchmark(check_speed=True,
              check_energy=True,
              check_time=True,
              check_smoothness=True,
              check_consistency=True,
              check_robustness=True,
              check_sensitivity=True,
              check_torque_limit=True,
              save_path="benchmark.yml")
```

The individual checks can be turned off. The results will be stored in the file specified in save_path.

11.1.3 Usage

An example usage can be found in the examples folder in the `benchmark_controller.py` script.
https://github.com/dfki-ric-underactuated-lab/torque_limited_simple_pendulum/blob/master/software/python/examples/benchmark_controller.py

11.2 Plotting Controllers

Controllers can be plotted by plotting their control signal in the pendulum's state space.

11.2.1 API

A controller inheriting from the `abstract controller` class can be plotted by using:

```
from simple_pendulum.analysis.plot_policy import plot_policy

plot_policy(controller,
            position_range=[-3.14, 3.14],
            velocity_range=[-2., 2.],
            samples_per_dim=100,
            plotstyle="3d",
            save_path=None)
```

The `plotstyle` can also be set to "2d". If a `save_path` is specified the plot will be stored in that location.

11.2.2 Usage

An example usage can be found in the `examples` folder in the `plot_controller.py` script.

CHAPTER TWELVE

SIMULATOR

The simulator class can simulate and animate the pendulum motion forward in time. The gym environment can be used for reinforcement learning.

12.1 API

12.1.1 The simulator

The simulator should be initialized with a plant (here the `PendulumPlant`) as follows:

```
pendulum = PendulumPlant()  
sim = Simulator(plant=pendulum)
```

To simulate the dynamics of the plant forward in time call:

```
T, X, TAU = sim.simulate(t0=0.0,  
                         x0=[0.5, 0.0],  
                         tf=10.0,  
                         dt=0.01,  
                         controller=None,  
                         integrator="runge_kutta")
```

The inputs of the function are:

- **t0**: float, start time, unit: s
- **x0**: start state (dimension as the plant expects it)
- **tf**: float, final time, unit: s
- **dt**: float, time step, unit: s
- **controller**: controller that computes the motor torque(s) to be applied. The controller should have the structure of the `AbstractController` class in `utilities/abstract_controller`. If `controller=None`, no controller is used and the free system is simulated.
- **integrator**: string, `euler` for euler integrator, `runge_kutta` for Runge-Kutta integrator

The function returns three lists:

- **T**: List of time values
- **X**: List of states
- **TAU**: List of actuations

The same simulation can be executed together with an animation of the plant (only implemented for 2d serial chains). For the simulation with animation call:

```
T, X, TAU = sim.simulate_and_animate(t0=0.0,
                                       x0=[0.5, 0.0],
                                       tf=10.0,
                                       dt=0.01,
                                       controller=None,
                                       integrator="runge_kutta",
                                       phase_plot=True,
                                       save_video=False,
                                       video_name="")
```

The additional parameters are:

- **phase_plot: bool**
 Whether to show a phase plot along the animation plot
- **save_video: bool**
 Whether to save the animation as mp4 video
- **video_name: string**
 Name of the file where the video should be saved (only used if save_video=True)

12.1.2 The gym environment

The environment can be initialized with:

```
pendulum = PendulumPlant()
sim = Simulator(plant=pendulum)
env = SimplePendulumEnv(simulator=sim,
                        max_steps=5000,
                        target=[np.pi, 0.0],
                        state_target_epsilon=[1e-2, 1e-2],
                        reward_type='continuous',
                        dt=1e-3,
                        integrator='runge_kutta',
                        state_representation=2,
                        validation_limit=-150,
                        scale_action=True,
                        random_init="False")
```

The parameters are:

- **simulator:**
 Simulator object

- **max_steps: int, default=``5000``**
Maximum steps the agent can take before the episode is terminated
- **target: array-like, default=[np.pi, 0.0]**
The target state of the pendulum
- **state_target_epsilon: array-like, default=[1e-2, 1e-2]**
Target epsilon for discrete reward type
- **reward_type: string, default=``continuous``**
The reward type selects the reward function which is used Options: continuous, discrete, soft_binary, soft_binary_with_repellor
- **dt: float, default=``1e-3``**
Timestep for the simulation
- **integrator: string, default='runge_kutta'**
The integrator which is used by the simulator Options: euler, runge_kutta
- **state_representation: int, default=``2``**
Determines how the state space of the pendulum is represented 2 means state = [position, velocity] 3 means state = [cos(position), sin(position), velocity]
- **validation_limit: float, default=-150**
If the reward during validation episodes surpasses this value the training stops early
- **scale_action: bool, default=True**
Whether to scale the output of the model with the torque limit of the simulator's plant. If True the model is expected so return values in the intervall [-1, 1] as action.
- **random_init: string, default=``False``**
A string determining the random state initialisation False: The pendulum is set to [0, 0], start_vicinity: The pendulum position and velocity are set in the range [-0.31, -0.31], everywhere: The pendulum is set to a random state in the whole possible state space

12.2 Usage

For examples of usages of the simulator class check out the scripts in the [examples](#) folder.

The gym environment is used for example in the [ddpg training](#).

CHAPTER THIRTEEN

HOW TO CONTRIBUTE

If you want to contribute to the project, i.e. by designing new controllers, you are very welcome to do so.

If you implement a controller please consider the following guidelines:

1. Create a folder with a unique and descriptive name for your controller in `software/python/controllers`.
2. Make sure your controller inherits from the `AbstractController` class.
3. Create a `README.md` file in your controller directory in which you explain how the controller works and how it can be used.
4. Create a `requirements.txt` file where you list required packages that are not listed in the main `requirements` file of the project.

If you implement an offline trajectory optimization or reinforcement learning algorithm follow these guidelines:

1. Create a folder with a unique and descriptive name for your controller in `software/python/simple_pendulum/trajectory_optimization`.
2. Create a `README.md` file in your controller directory in which you explain how the method works and how it can be used.
3. Create a `requirements.txt` file where you list required packages that are not listed in the main `requirements` file of the project.
4. Either
 - (a) write a controller class which makes it possible to execute your policy in simulation and on the real system. Make sure it inherits from the `AbstractController` class.
 - (b) export your trajectory to a csv file and save it at `data/trajectories`. The columns of the csv file should be: time, position, velocity, control_inputs. The first line is reserved for a header. In this format the csv file can be simulated or applied to the real system with the `open_loop_controller` class

If you want to contribute software in another programming language besides python, create a new top level directory named after the programming language of your choice (eg, `./c++`) and try to follow the structure of the Python code as closely as possible, that will aid us when looking through it.

If you discover bugs, have feature requests, or want to improve the documentation, please open an issue at the issue tracker of the project.

If you want to contribute code, please open a pull request via GitHub by forking the project, committing changes to your fork, and then opening a pull request from your forked branch to the main branch of gmr.

CHAPTER
FOURTEEN

API REFERENCE

CHAPTER
FIFTEEN

ANALYSIS

CHAPTER SIXTEEN

BENCHMARKS

modify_pendulum_parameter (*par*)

Randomly modify a given parameter

class benchmarker (*dt=0.01, max_time=10.0, integrator='runge_kutta', benchmark_iterations=10*)

Bases: object

Benchmark class

init_pendulum (*mass=0.57288, length=0.5, inertia=None, damping=0.15, coulomb_friction=0.0, gravity=9.81, torque_limit=2.0*)

Initialize the pendulum parameters.

CHAPTER

SEVENTEEN

PARAMETERS

mass

[float, default=0.57288] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

inertia

[float, default=None] inertia of the pendulum [kg m^2] defaults to point mass inertia (mass*length^2)

damping

[float, default=0.15] damping factor of the pendulum [kg m/s]

coulomb_friction

[float, default=0.0] coulomb friction of the pendulum [Nm]

gravity

[float, default=9.81] gravity (positive direction points down) [m/s^2]

torque_limit

[float, default=2.0] the torque_limit of the pendulum actuator

set_controller (*controller*)

check_regular_execution ()

check_consistency ()

check_robustness ()

check_sensitivity ()

check_reduced_torque_limit (*tl*=*inf*)

check_speed (*N*=1000)

benchmark (*check_speed*=*True*, *check_energy*=*True*, *check_time*=*True*, *check_smoothness*=*True*,
check_consistency=*True*, *check_robustness*=*True*, *check_sensitivity*=*True*,
check_torque_limit=*True*, *save_path*=*None*)

CHAPTER
EIGHTEEN

POLICY PLOTS

```
plot_policy(controller, position_range=[-3.141592653589793, 3.141592653589793], velocity_range=[-8, 8], samples_per_dim=100, plotstyle='2d', save_path=None)
```

Plot controller policy

CHAPTER
NINETEEN

CONTROLLERS

CHAPTER TWENTY

ABSTRACT CONTROLLER

Abstract controller class to which all controller classes have to adhere.

class AbstractController

Bases: ABC

Abstract controller class. All controller should inherit from this abstract class.

abstract get_control_output(meas_pos, meas_vel, meas_tau, meas_time)

The function to compute the control input for the pendulum actuator. Supposed to be overwritten by actual controllers. The API of this method should be adapted. Unused inputs/outputs can be set to None.

Parameters

meas_pos: float

The position of the pendulum [rad]

meas_vel: float

The velocity of the pendulum [rad/s]

meas_tau: float

The measured torque of the pendulum [Nm]

meas_time: float

The collapsed time [s]

CHAPTER TWENTYONE

RETURNS

des_pos: float

The desired position of the pendulum [rad]

des_vel: float

The desired velocity of the pendulum [rad/s]

des_tau: float

The torque supposed to be applied by the actuator [Nm]

init (x0)

Initialize the controller. May not be necessary.

CHAPTER TWENTYTWO

PARAMETERS

x0: array like

The start state of the pendulum

set_goal (x)

Set the desired state for the controller. May not be necessary.

CHAPTER TWENTYTHREE

PARAMETERS

x: array like

The desired goal state of the controller

```
ak80_6(controller, kp=0.0, kd=0.0, torque_limit=1.0, dt=0.005, tf=10.0, motor_id=1,  
motor_type='AK80_6_VIpI', can_port='can0')
```

CHAPTER
TWENTYFOUR

MOTOR CONTROL LOOP

The motor control loop only contains the minimum of code necessary to send commands to and receive measurement data from the motor control board in real time over CAN bus. It specifies the outgoing CAN port and the CAN ID of the motor on the CAN bus and transfers this information to the motor driver. It furthermore requires the following arguments:

The return values start, end and meas_dt are required to monitor if desired and measured time steps match.

24.1 Parameters

controller

[controller object inheriting from the abstract controller class] Calls the controller, which executes the respective control policy and returns the input torques

kp

[float, default=0.0] Weight for position control

kd

[float, default=0.0] Weight for velocity control

torque_limit

[float default=1.0] torque limit for the motor [Nm]

dt

[float, default=0.005] time step in control loop [s]

tf

[float, default=10.0] length of the experiment [s]

motor_id

[int, default=1] id of the used motor

motor_type

[string, default='AK80_6_V1p1'] type of the motor

can_port

[string, default='can0'] can port for motor communication

24.2 Returns

start

[float,] start time of experiment

end

[float] end time of experiment

meas_dt

[float] measured time step

data_dict

[dict] dictionary containing the recorded data

CHAPTER
TWENTYFIVE

DEEP DETERMINISTIC POLICY GRADIENT CONTROL

CHAPTER

TWENTYSIX

DDPG CONTROLLER

```
class ddpg_controller(model_path, torque_limit, state_representation=3)
```

Bases: *AbstractController*

DDPG controller class

```
get_control_output(meas_pos, meas_vel, meas_tau=0, meas_time=0)
```

The function to compute the control input for the pendulum actuator. Supposed to be overwritten by actual controllers. The API of this method should be adapted. Unused inputs/outputs can be set to None.

Parameters

meas_pos: float

The position of the pendulum [rad]

meas_vel: float

The velocity of the pendulum [rad/s]

meas_tau: float

The measured torque of the pendulum [Nm]

meas_time: float

The collapsed time [s]

CHAPTER
TWENTYSEVEN

RETURNS

des_pos: float

The desired position of the pendulum [rad]

des_vel: float

The desired velocity of the pendulum [rad/s]

des_tau: float

The torque supposed to be applied by the actuator [Nm]

get_observation (state)

CHAPTER
TWENTYEIGHT

ENERGY SHAPING CONTROL

CHAPTER
TWENTYNINE

ENERGY SHAPING CONTROLLER

```
class EnergyShapingController(mass=1.0, length=0.5, damping=0.1, gravity=9.81,  
                               torque_limit=2.0, k=1.0)
```

Bases: *AbstractController*

Controller which swings up the pendulum by regulating its energy.

Parameters

mass

[float, default=1.0] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

damping

[float, default=0.1] damping factor of the pendulum [kg m/s]

gravity

[float, default=9.81] gravity (positive direction points down) [m/s²]

torque_limit

[float, default=2.0] torque limit of the motor [Nm]

k

[float, default=1.0] the weight determining the output torque with respect to the current energy level.

set_goal (x)

Set the goal for the controller. This function calculates the energy of the goal state.

CHAPTER THIRTY

PARAMETERS

x

[array-like] the goal state for the pendulum

get_control_output (*meas_pos*, *meas_vel*, *meas_tau=0*, *meas_time=0*)

The function to compute the control input for the pendulum actuator

CHAPTER
THIRTYONE

PARAMETERS

meas_pos

[float] the position of the pendulum [rad]

meas_vel

[float] the velocity of the pendulum [rad/s]

meas_tau

[float] the measured torque of the pendulum [Nm] (not used)

meas_time

[float] the collapsed time [s] (not used)

CHAPTER

THIRTYTWO

RETURNS

des_pos

[float] the desired position of the pendulum [rad] (not used, returns None)

des_vel

[float] the desired velocity of the pendulum [rad/s] (not used, returns None)

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

```
class EnergyShapingAndLQRController(mass=1.0, length=0.5, damping=0.1, coulomb_fric=0.0,  
                                     gravity=9.81, torque_limit=inf, k=1.0, Q=array([[10, 0],  
                                         [0, 1]]), R=array([[1]]), compute_RoA=False)
```

Bases: *AbstractController*

Controller which swings up the pendulum with the energy shaping controller and stabilizes the pendulum with the lqr controller.

CHAPTER THIRTYTHREE

PARAMETERS

mass

[float, default=1.0] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

damping

[float, default=0.1] damping factor of the pendulum [kg m/s]

coulomb_fric

[float, default=0.0] friction term, (independent of magnitude of velocity), unit: Nm

gravity

[float, default=9.81] gravity (positive direction points down) [m/s^2]

torque_limit

[float, default=np.inf] the torque_limit of the pendulum actuator

k

[float, default=1.0] (energy controller) the weight determining the output torque with respect to the current energy level.

Q

[array-like, default=np.diag(10, 1)] (LQR controller) the state cost matrix, np.shape(Q) = (2,2)

R

[array-like, default=np.array([[1]])] (LQR controller) the control cost matrix, np.shape(R) = (1,1)

compute_RoA

[bool, default=False] (LQR controller) whether to compute the region of attraction of the LQR controller (requires drake)

set_goal (x)

Set the goal for the controller.

33.1 Parameters

x

[array-like] the goal state for the pendulum

get_control_output (*meas_pos*, *meas_vel*, *meas_tau*=0, *meas_time*=0, *verbose*=False)

The function to compute the control input for the pendulum actuator

33.2 Parameters

meas_pos

[float] the position of the pendulum [rad]

meas_vel

[float] the velocity of the pendulum [rad/s]

meas_tau

[float] the measured torque of the pendulum [Nm] (not used)

meas_time

[float] the collapsed time [s] (not used)

verbose

[bool, default=False] whether to print when the controller switches between energy shaping and lqr

33.3 Returns

des_pos

[float] the desired position of the pendulum [rad] (not used, returns None)

des_vel

[float] the desired velocity of the pendulum [rad/s] (not used, returns None)

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

CHAPTER THIRTYFOUR

UNIT TESTS

```
class Test (methodName='runTest')
```

Bases: TestCase

Create an instance of the class that will use the named test method when executed. Raises a ValueError if the instance does not have a method with the specified name.

```
epsilon = 0.2
```

```
test_0_energy_shaping_swingup()
```

CHAPTER
THIRTYFIVE

CONTROLLERS

CHAPTER
THIRTYSIX

GRAVITY COMPENSATION CONTROL

CHAPTER
THIRTYSEVEN

GRAVITY COMPENSATION CONTROLLER

```
class GravityCompController (params)
```

Bases: *AbstractController*

```
get_control_output (meas_pos, meas_vel, meas_tau, meas_time)
```

The function to compute the control input for the pendulum actuator. Supposed to be overwritten by actual controllers. The API of this method should be adapted. Unused inputs/outputs can be set to None.

Parameters

meas_pos: float

The position of the pendulum [rad]

meas_vel: float

The velocity of the pendulum [rad/s]

meas_tau: float

The measured torque of the pendulum [Nm]

meas_time: float

The collapsed time [s]

CHAPTER THIRTYEIGHT

RETURNS

des_pos: float

The desired position of the pendulum [rad]

des_vel: float

The desired velocity of the pendulum [rad/s]

des_tau: float

The torque supposed to be applied by the actuator [Nm]

CHAPTER
THIRTYNINE

ILQR MODEL PREDICTIVE CONTROL

CHAPTER
FORTY

ILQR MPC CONTROLLER

```
class iLQRMPCController(mass=0.5, length=0.5, damping=0.15, coulomb_friction=0.0, gravity=9.81,
                           inertia=0.125, dt=0.01, n=50, max_iter=1, break_cost_redu=1e-06,
                           sCu=10.0, sCp=0.001, sCv=0.001, sCen=0.0, fCp=1000.0, fCv=10.0,
                           fCen=300.0, dynamics='runge_kutta', n_x=3)
```

Bases: *AbstractController*

Controller which computes an ilqr solution at every timestep and uses the first control output.

CHAPTER FORTYONE

PARAMETERS

mass

[float, default=1.0] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

damping

[float, default=0.1] damping factor of the pendulum [kg m/s]

coulomb_friction

[float, default=0.0] coulomb_friciton term of the pendulum

gravity

[float, default=9.81] gravity (positive direction points down) [m/s^2]

inertia

[float, default=0.125] inertia of the pendulum

dt

[float, default=0.01] timestep of the simulation

n

[int, default=50] number of timnesteps the controller optimizes ahead

max_iter

[int, default=1] optimization iterations the alogrithm makes at every timestep

break_cost_redu

[float, default=1e-6] cost at which the optimization breaks off early

sCu

[float, default=10.0] running cost weight for the control input u

sCp

[float, default=0.001] running cost weight for the position error

sCv

[float, default=0.001] running cost weight for the velocity error

sCen

[float, default=0.0] running cost weight for the energy error

fCp

[float, default=1000.0] final cost weight for the position error

fCv

[float, default=10.0] final cost weight for the velocity error

fCen

[float, default=300.0] final cost weight for the energy error

dynamics

[string, default="runge_kutta"] string that selects the integrator to be used for the simulation options are: "euler", "runge_kutta"

n_x

[int, default=3] determines how the state space of the pendulum is represented n_x=2 means state = [position, velocity] n_x=3 means state = [cos(position), sin(position), velocity]

init (x0)

Initialize the controller. May not be necessary.

41.1 Parameters

x0: array like

The start state of the pendulum

load_initial_guess (filepath='Pendulum_data/trajectory.csv', verbose=True)

load initial guess trajectory from file

41.2 Parameters

filepath

[string, default="Pendulum_data/trajectory.csv"] path to the csv file containing the initial guess for the trajectory

verbose

[bool, default=True] whether to print from where the initial guess is loaded

set_initial_guess (u_trj=None, x_trj=None)

set initial guess from array like object

41.3 Parameters

u_trj

[array-like, default=None] initial guess for control inputs u ignored if u_trj==None

x_trj

[array-like, default=None] initial guess for state space trajectory ignored if x_trj==None

compute_initial_guess (N=None, verbose=True)

compute initial guess

41.4 Parameters

N

[int, default=None] number of timesteps to plan ahead if N==None, N defaults to the number of timesteps that is also used during the online optimization (n in the class __init__)

verbose

[bool, default=True] whether to print when the initial guess calculation is finished

set_goal (x)

Set a goal for the controller. Initializes the cost functions.

41.5 Parameters

x

[array-like] goal state for the pendulum

get_control_output (meas_pos, meas_vel, meas_tau=0, meas_time=0)

The function to compute the control input for the pendulum actuator

41.6 Parameters

meas_pos

[float] the position of the pendulum [rad]

meas_vel

[float] the velocity of the pendulum [rad/s]

meas_tau

[float, default=0] the measured torque of the pendulum [Nm] (not used)

meas_time

[float, default=0] the collapsed time [s] (not used)

41.7 Returns

des_pos

[float] the desired position of the pendulum [rad] (not used, returns None)

des_vel

[float] the desired velocity of the pendulum [rad/s] (not used, returns None)

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

CHAPTER
FORTYTWO

UNIT TESTS

```
class Test (methodName='runTest')
```

Bases: TestCase

Create an instance of the class that will use the named test method when executed. Raises a ValueError if the instance does not have a method with the specified name.

```
epsilon = 0.2
```

```
test_0_iLQR_MPC.swingup_nx2()
```

```
test_1_iLQR_MPC.swingup_nx3()
```

CHAPTER
FORTYTHREE

LINEAR QUADRATIC REGULATOR (LQR)

CHAPTER

FORTYFOUR

LQR SOLVER

Adapted from Mark [Wilfried Mueller](#)

lqr (A, B, Q, R)

Solve the continuous time lqr controller. $dx/dt = A x + B u$ cost = integral $x.T^*Q*x + u.T^*R*u$ ref: Bertsekas, p.151

dlqr (A, B, Q, R)

Solve the discrete time lqr controller. $x[k+1] = A x[k] + B u[k]$ cost = sum $x[k].T^*Q*x[k] + u[k].T^*R*u[k]$ ref: Bertsekas, p.151

CHAPTER

FORTYFIVE

LQR CONTROLLER

```
class LQRController(mass=1.0, length=0.5, inertia=None, damping=0.1, coulomb_fric=0.0,
                     gravity=9.81, torque_limit=inf, Q=array([[10, 0], [0, 1]]), R=array([[1]]),
                     compute_RoA=False)
```

Bases: *AbstractController*

Controller which stabilizes the pendulum at its instable fixpoint. Parameters ————— mass : float, default=1.0

mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

damping

[float, default=0.1] damping factor of the pendulum [kg m/s]

coulomb_fric

[float, default=0.0] friction term, (independent of magnitude of velocity), unit: Nm

gravity

[float, default=9.81] gravity (positive direction points down) [m/s²]

torque_limit

[float, default=np.inf] the torque_limit of the pendulum actuator

Q

[array-like, default=np.diag(10, 1)] the state cost matrix, np.shape(Q) = (2,2)

R

[array-like, default=np.array([[1]])] the control cost matrix, np.shape(R) = (1,1)

compute_RoA

[bool, default=False] whether to compute the region of attraction of the LQR controller (requires drake)

set_goal (*goal*)

Set the desired state for the controller. May not be necessary.

CHAPTER

FORTYSIX

PARAMETERS

x: array like

The desired goal state of the controller

set_clip()**get_control_output (meas_pos, meas_vel, meas_tau=0, meas_time=0)**

The function to compute the control input for the pendulum actuator Parameters ----- meas_pos : float

the position of the pendulum [rad]

meas_vel

[float] the velocity of the pendulum [rad/s]

meas_tau

[float, default=0] the measured torque of the pendulum [Nm] (not used)

meas_time

[float, default=0] the collapsed time [s] (not used)

CHAPTER FORTYSEVEN

RETURNS

des_pos

[float] the desired position of the pendulum [rad] (not used, returns None)

des_vel

[float] the desired velocity of the pendulum [rad/s] (not used, returns None)

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

CHAPTER

FORTYEIGHT

UNIT TESTS

```
class Test (methodName='runTest')
```

Bases: TestCase

Create an instance of the class that will use the named test method when executed. Raises a ValueError if the instance does not have a method with the specified name.

```
epsilon = 0.01
```

```
test_0_LQR_stabilization()
```

```
transform(q)
```

```
class analytic_roa (mass=1.0, length=0.5, damping=0.1, gravity=9.81, torque_limit=inf, Q_11=1, Q_22=1, R=I)
```

Bases: object

```
tstar(q)
```

```
u(t, q)
```

```
satisfies_theory(y)
```

```
satisfies_theory_full(y)
```

```
class najafi_oracle (plant, controller, n=100000)
```

Bases: object

```
query(q)
```

```
get_ellipse_params(rho, M)
```

Returns ellipse params (excl center point)

```
get_ellipse_patch(px, py, rho, M, alpha_val=1, linec='red', facec='none', linestyle='solid')
```

return an ellipse patch

```
plot_ellipse(px, py, rho, M, save_to=None, show=True)
```

na jafi based sampling (*plant, controller, n=10000, rho0=100, M=None, x_star=array([3.14159265, 0.0])*)

Estimate the RoA for the closed loop dynamics using the method introduced in Najafi, E., Babuška, R. & Lopes, G.A.D. A fast sampling method for estimating the domain of attraction. Nonlinear Dyn 86, 823–834 (2016). <https://doi.org/10.1007/s11071-016-2926-7>

CHAPTER

FORTYNINE

PARAMETERS

plant

[simple_pendulum.model.pendulum_plant] configured pendulum plant object

controller

[simple_pendulum.controllers.lqr.lqr_controller] configured lqr controller object

n

[int, optional] number of samples, by default 100000

rho0

[int, optional] initial estimate of rho, by default 10

M

[np.array, optional] M, such that $x_{\bar{}}^T M x_{\bar{}}$ is the Lyapunov fct. by default None, and controller.S is used

x_star

[np.array, optional] nominal position (fixed point of the nonlinear dynamics)

CHAPTER
FIFTY

RETURNS

rho

[float] estimated value of rho

M

[np.array] M

SOSequalityConstrained(*pendulum, controller*)

Estimate the RoA for the closed loop dynamics using the method described by Russ Tedrake in “Underactuated Robotics: Algorithms for Walking, Running, Swimming, Flying, and Manipulation”,

Course Notes for MIT 6.832, 2022, “<http://underactuated.mit.edu>”, sec. 9.3.2: “The equality-constrained formulation”. This is discussed a bit more by Shen Shen and Russ Tedrake in “Sampling Quotient-Ring Sum-of-Squares Programs for Scalable Verification of Nonlinear Systems”, Proceedings of the 2020 59th IEEE Conference on Decision and Control (CDC) , 2020., http://groups.csail.mit.edu/robotics-center/public_papers/Shen20.pdf, pg. 2-3.

CHAPTER FIFTYONE

PARAMETERS

pendulum

[simple_pendulum.model.pendulum_plant] configured pendulum plant object

controller

[simple_pendulum.controllers.lqr.lqr_controller] configured lqr controller object

CHAPTER FIFTYTWO

RETURNS

rho

[float] estimated value of rho

S

[np.array] S matrix from the lqr controller

soslineSearch (*pendulum, controller*)

Simple line search(bisection method) on rho that search for the maximum rho which satisfies the Lyapunov conditions in order to obtain an estimate of the RoA for the closed loop dynamics.

CHAPTER FIFTYTHREE

PARAMETERS

pendulum

[simple_pendulum.model.pendulum_plant] configured pendulum plant object

controller

[simple_pendulum.controllers.lqr.lqr_controller] configured lqr controller object

CHAPTER
FIFTYFOUR

RETURNS

rho

[float] estimated value of rho

S

[np.array] S matrix from the lqr controller

direct_sphere(*d*, *r_i*=0, *r_o*=1)

Direct Sampling from the *d* Ball based on Krauth, Werner. Statistical Mechanics: Algorithms and Computations. Oxford Master Series in Physics 13. Oxford: Oxford University Press, 2006. page 42

CHAPTER FIFTYFIVE

PARAMETERS

d

[int] dimension of the ball

r_i

[int, optional] inner radius, by default 0

r_o

[int, optional] outer radius, by default 1

CHAPTER FIFTYSIX

RETURNS

np.array

random vector directly sampled from the solid d Ball

sample_from_ellipsoid($M, rho, r_i=0, r_o=1$)

sample directly from the ellipsoid defined by $x^T M x$.

CHAPTER FIFTYSEVEN

PARAMETERS

M

[np.array] Matrix M such that $x^T M x \leq \rho$ defines the hyperellipsoid to sample from

rho

[float] rho such that $x^T M x \leq \rho$ defines the hyperellipsoid to sample from

r_i

[int, optional] inner radius, by default 0

r_o

[int, optional] outer radius, by default 1

CHAPTER
FIFTYEIGHT

RETURNS

np.array

random vector from within the hyperellipsoid

quad_form(M, x)

Helper function to compute quadratic forms such as $x^T M x$

vol_ellipsoid(ρ, M)

Calculate the Volume of a Hyperellipsoid Volume of the Hyperellipsoid according to <https://math.stackexchange.com/questions/332391/volume-of-hyperellipsoid/332434> Intuition: <https://textbooks.math.gatech.edu/ila/determinants-volumes.html> Volume of n-Ball https://en.wikipedia.org/wiki/Volume_of_an_n-ball

rhoVerification($\rho, \text{pendulum}, \text{controller}$)

SOS Verification of the Lyapunov conditions for a given rho in order to obtain an estimate of the RoA for the closed loop dynamics.

This method is described by Russ Tedrake in “Underactuated Robotics: Algorithms for Walking, Running, Swimming, Flying, and Manipulation”, Course Notes for MIT 6.832, 2022, “<http://underactuated.mit.edu>”, sec. 9.3.2: “Basic region of attraction formulation”.

CHAPTER
FIFTYNINE

PARAMETERS

rho: float

value of rho to be verified

pendulum

[simple_pendulum.model.pendulum_plant] configured pendulum plant object

controller

[simple_pendulum.controllers.lqr.lqr_controller] configured lqr controller object

CHAPTER SIXTY

RETURNS

result

[boolean] result of the verification

```
class PendulumPlantApprox (mass=1.0, length=0.5, damping=0.1, gravity=9.81, coulomb_fric=0.0,  
                           inertia=None, torque_limit=inf, taylorApprox_order=1)
```

Bases: object

The PendulumPlantApprox class contains the taylor-approximated dynamics of the simple pendulum.

The state of the pendulum in this class is described by

state = [angle, angular velocity] (array like with len(state)=2) in units: rad and rad/s

The zero state of the angle corresponds to the pendulum hanging down. The plant expects an actuation input (tau) either as float or array like in units Nm. (in which case the first entry is used (which should be a float))

CHAPTER SIXTYONE

PARAMETERS

mass

[float, default=1.0] pendulum mass, unit: kg

length

[float, default=0.5] pendulum length, unit: m

damping

[float, default=0.1] damping factor (proportional to velocity), unit: kg*m/s

gravity

[float, default=9.81] gravity (positive direction points down), unit: m/s²

coulomb_fric

[float, default=0.0] friction term, (independent of magnitude of velocity), unit: Nm

inertia

[float, default=None] inertia of the pendulum (defaults to point mass inertia) unit: kg*m²

torque_limit: float, default=np.inf

maximum torque that the motor can apply, unit: Nm

taylorApprox_order: int, default=1

order of the taylor approximation of the sine term

forward_dynamics (state, tau)

Computes forward dynamics

61.1 Parameters

state

[array like] len(state)=2 The state of the pendulum [angle, angular velocity] floats, units: rad, rad/s

tau

[float] motor torque, unit: Nm

61.2 Returns

- float, angular acceleration, unit: rad/s²

rhs (*t, state, tau*)

Computes the integrand of the equations of motion.

61.3 Parameters

t

[float] time, not used (the dynamics of the pendulum are time independent)

state

[array like] len(state)=2 The state of the pendulum [angle, angular velocity] floats, units: rad, rad/s

tau

[float or array like] motor torque, unit: Nm

61.4 Returns

res

[array like] the integrand, contains [angular velocity, angular acceleration]

CHAPTER
SIXTYTWO

OPEN LOOP CONTROL

CHAPTER SIXTYTHREE

OPEN LOOP CONTROLLER

```
class OpenLoopController(data_dict)
```

Bases: *AbstractController*

Controller acts on a predefined trajectory.

CHAPTER SIXTYFOUR

PARAMETERS

data_dict

[dictionary] a dictionary containing the trajectory to follow should have the entries:
data_dict[“des_time_list”] : desired timesteps data_dict[“des_pos_list”] : desired positions
data_dict[“des_vel_list”] : desired velocities data_dict[“des_tau_list”] : desired torques

init (x0)

Initialize the controller. May not be necessary.

64.1 Parameters

x0: array like

The start state of the pendulum

set_goal (x)

Set the desired state for the controller. May not be necessary.

64.2 Parameters

x: array like

The desired goal state of the controller

get_control_output (meas_pos=None, meas_vel=None, meas_tau=None, meas_time=None)

The function to read and send the entries of the loaded trajectory as control input to the simulator/real pendulum.

64.3 Parameters

meas_pos

[float, default=None] the position of the pendulum [rad]

meas_vel

[float, default=None] the velocity of the pendulum [rad/s]

meas_tau

[float, default=None] the measured torque of the pendulum [Nm]

meas_time

[float, default=None] the collapsed time [s]

64.4 Returns

des_pos

[float] the desired position of the pendulum [rad]

des_vel

[float] the desired velocity of the pendulum [rad/s]

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

```
class OpenLoopAndLQRController (data_dict, mass=1.0, length=0.5, damping=0.1, gravity=9.81,  
                                torque_limit=inf)
```

Bases: *AbstractController*

Controller acts on a predefined trajectory. Switches to lqr control when in its region of attraction.

CHAPTER SIXTYFIVE

PARAMETERS

data_dict

[dictionary] a dictionary containing the trajectory to follow should have the entries:
data_dict[“des_time_list”] : desired timesteps data_dict[“des_pos_list”] : desired positions
data_dict[“des_vel_list”] : desired velocities data_dict[“des_tau_list”] : desired torques

mass

[float, default=1.0] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

damping

[float, default=0.1] damping factor of the pendulum [kg m/s]

gravity

[float, default=9.81] gravity (positive direction points down) [m/s²]

torque_limit

[float, default=np.inf] the torque_limit of the pendulum actuator

init (x0)

Initialize the controller. May not be necessary.

65.1 Parameters

x0: array like

The start state of the pendulum

set_goal (x)

Set the desired state for the controller. May not be necessary.

65.2 Parameters

x: array like

The desired goal state of the controller

get_control_output (meas_pos, meas_vel, meas_tau=0, meas_time=0, verbose=False)

The function to read and send the entries of the loaded trajectory as control input to the simulator/real pendulum. Switches to lqr control when in its region of attraction.

65.3 Parameters

meas_pos

[float] the position of the pendulum [rad]

meas_vel

[float] the velocity of the pendulum [rad/s]

meas_tau

[float, default=0] the measured torque of the pendulum [Nm]

meas_time

[float, default=0] the collapsed time [s]

verbose

[bool, default=False] whether to print when the controller switches between preloaded trajectory and lqr

65.4 Returns

des_pos

[float] the desired position of the pendulum [rad]

des_vel

[float] the desired velocity of the pendulum [rad/s]

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

CHAPTER
SIXTYSIX

PROPORTIONAL-INTEGRAL-DERIVATIVE (PID) CONTROL

CHAPTER SIXTYSEVEN

PID CONTROLLER

```
class PIDController(data_dict, Kp, Ki, Kd, use_feed_forward=True)
```

Bases: *AbstractController*

Controller acts on a predefined trajectory and adds PID control gains.

CHAPTER

SIXTYEIGHT

PARAMETERS

data_dict

[dictionary] a dictionary containing the trajectory to follow should have the entries:
data_dict[“des_time_list”] : desired timesteps data_dict[“des_pos_list”] : desired positions
data_dict[“des_vel_list”] : desired velocities data_dict[“des_tau_list”] : desired torques

Kp

[float] proportional term, gain proportional to the position error

Ki

[float] integral term, gain proportional to the integral of the position error

Kd

[float] derivative term, gain proportional to the derivative of the position error

use_feed_forward

[bool] whether to use the torque that is provided in the csv file

init (x0)

Initialize the controller. May not be necessary.

68.1 Parameters

x0: array like

The start state of the pendulum

set_goal (x)

Set the desired state for the controller. May not be necessary.

68.2 Parameters

x: array like

The desired goal state of the controller

get_control_output (meas_pos=None, meas_vel=None, meas_tau=None, meas_time=None)

The function to read and send the entries of the loaded trajectory as control input to the simulator/real pendulum.

68.3 Parameters

meas_pos

[float, default=None] the position of the pendulum [rad]

meas_vel

[float, default=None] the velocity of the pendulum [rad/s]

meas_tau

[float, default=None] the measured torque of the pendulum [Nm]

meas_time

[float, default=None] the collapsed time [s]

68.4 Returns

des_pos

[float] the desired position of the pendulum [rad]

des_vel

[float] the desired velocity of the pendulum [rad/s]

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

CHAPTER
SIXTYNINE

SOFT ACTOR CRITIC (SAC) CONTROL

CHAPTER SEVENTY

SAC CONTROLLER

```
class SacController(model_path, torque_limit, use_symmetry=True, state_representation=2)
```

Bases: *AbstractController*

Controller which acts on a policy which has been learned with sac.

CHAPTER

SEVENTYONE

PARAMETERS

model_path

[string] path to the trained model in zip format

torque_limit

[float] torque limit of the pendulum. The output of the model will be scaled with this number

use_symmetry

[bool] whether to use the left/right symmetry of the pendulum

get_control_output (meas_pos, meas_vel, meas_tau=0, meas_time=0)

The function to compute the control input for the pendulum actuator

71.1 Parameters

meas_pos

[float] the position of the pendulum [rad]

meas_vel

[float] the velocity of the pendulum [rad/s]

meas_tau

[float] the measured torque of the pendulum [Nm] (not used)

meas_time

[float] the collapsed time [s] (not used)

71.2 Returns

des_pos

[float] the desired position of the pendulum [rad] (not used, returns None)

des_vel

[float] the desired velocity of the pendulum [rad/s] (not used, returns None)

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

get_observation (*state*)

CHAPTER
SEVENTYTWO

TIME-VARYING LINEAR QUADRATIC REGULATOR (TVLQR)

CHAPTER SEVENTYTHREE

TVLQR CONTROLLER

```
class TVLQRController(data_dict, mass=1.0, length=0.5, damping=0.1, gravity=9.81,  
                      torque_limit=inf)
```

Bases: *AbstractController*

Controller acts on a predefined trajectory.

CHAPTER

SEVENTYFOUR

PARAMETERS

data_dict

[dictionary] a dictionary containing the trajectory to follow should have the entries:
data_dict[“des_time_list”] : desired timesteps data_dict[“des_pos_list”] : desired positions
data_dict[“des_vel_list”] : desired velocities data_dict[“des_tau_list”] : desired torques

mass

[float, default=1.0] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

damping

[float, default=0.1] damping factor of the pendulum [kg m/s]

gravity

[float, default=9.81] gravity (positive direction points down) [m/s²]

torque_limit

[float, default=np.inf] the torque_limit of the pendulum actuator

init (x0)

Initialize the controller. May not be necessary.

74.1 Parameters

x0: array like

The start state of the pendulum

set_goal (x)

Set the desired state for the controller. May not be necessary.

74.2 Parameters

x: array like

The desired goal state of the controller

get_control_output (meas_pos=None, meas_vel=None, meas_tau=None, meas_time=None)

The function to read and send the entries of the loaded trajectory as control input to the simulator/real pendulum.

74.3 Parameters

meas_pos

[float, default=None] the position of the pendulum [rad]

meas_vel

[float, default=None] the velocity of the pendulum [rad/s]

meas_tau

[float, default=None] the measured torque of the pendulum [Nm]

meas_time

[float, default=None] the collapsed time [s]

74.4 Returns

des_pos

[float] the desired position of the pendulum [rad]

des_vel

[float] the desired velocity of the pendulum [rad/s]

des_tau

[float] the torque supposed to be applied by the actuator [Nm]

set_Qf (Qf)

This function is useful only for RoA purposes. Used to set the final S-matrix of the tvlqr controller.

74.5 Parameters

Qf

[matrix] the S-matrix from time-invariant RoA estimation around the up-right position.

get_ellipse_params (*rho, M*)

Returns ellipse params (excl center point)

get_ellipse_patch (*px, py, rho, M, alpha_val=1, linec='red', facec='none', linest='solid'*)

return an ellipse patch

plot_ellipse (*px, py, rho, M, save_to=None, show=True*)

plotFirstLastEllipses (*funnel_path, traj_path*)

plotRhoEvolution (*funnel_path, traj_path*)

plotFunnel3d (*csv_path, traj_path, ax*)

Function to draw a discrete 3d funnel plot. Basically we are plotting a 3d ellipse patch in each knot point.

Parameters ——— *rho* : np.array

array that contains the estimated rho value for all the knot points

S: np.array

array of matrices that define ellipses in all the knot points, from tvlqr controller.

x0: np.array

pre-computed nominal trajectory

time: np.array

time array related to the nominal trajectory

ax: matplotlib.axes

axes of the plot where we want to add the 3d funnel plot, useful in the verification function.

plotFunnel (*funnel_path, traj_path, ax=None*)

Function to draw a continue 2d funnel plot. This implementation makes use of the convex hull concept as done in the MATLAB code of the Robot Locomotion Group (<https://groups.csail.mit.edu/locomotion/software.html>). Parameters ——— *rho* : np.array

array that contains the estimated rho value for all the knot points

S: np.array

array of matrices that define ellipses in all the knot points, from tvlqr controller.

x0: np.array

pre-computed nominal trajectory

time: np.array

time array related to the nominal trajectory

TVrhoVerification (*pendulum, controller, funnel_path, traj_path, nSimulations, ver_idx*)

Function to verify the time-variant RoA estimation. This implementation permitts also to choose which knot has to be tested. Furthermore the a 3d funnel plot has been implemented.

CHAPTER

SEVENTYFIVE

PARAMETERS

pendulum: simple_pendulum.model.pendulum_plant
configured pendulum plant object

controller: simple_pendulum.controllers.tvlqr.tvlqr
configured tvlqr controller object

x0_t: np.array
pre-computed nominal trajectory

time: np.array
time array related to the nominal trajectory

nSimulations: int
number of simulations for the verification

ver_idx: int
knot point to be verified

funnel2DComparison (*csv_pathFunnelSos*, *csv_pathFunnelProb*, *traj_path*)

rhoComparison (*csv_pathFunnelSos*, *csv_pathFunnelProb*)

TVprobRhoComputation (*pendulum*, *controller*, *x0_t*, *time*, *N*, *nSimulations*, *rhof*)

Function to perform the time-variant RoA estimation. This implementation has been inspired by “Feedback-Motion-Planning with Simulation-Based LQR-Trees” by Philipp Reist, Pascal V. Preiswerk and Russ Tedrake (https://groups.csail.mit.edu/robotics-center/public_papers/Reist15.pdf).

CHAPTER
SEVENTYSIX

PARAMETERS

pendulum: simple_pendulum.model.pendulum_plant
configured pendulum plant object

controller: simple_pendulum.controllers.tvlqr.tvlqr
configured tvlqr controller object

x0_t: np.array
pre-computed nominal trajectory

time: np.array
time array related to the nominal trajectory

N: int
number of considered knot points

nSimulations: int
max number of simulations for each ellipse estimation

rhof: float
final rho value, from the time-invariant RoA estimation

CHAPTER SEVENTYSEVEN

RETURNS

rho

[np.array] array that contains the estimated rho value for all the knot points

S: np.array

array that contains the S matrix in each knot point

TVsosRhoComputation (*pendulum, controller, time, N, rhof*)

Bilinear alternationturn used for the SOS funnel estimation.

CHAPTER SEVENTYEIGHT

PARAMETERS

pendulum: simple_pendulum.model.pendulum_plant

configured pendulum plant object

controller: simple_pendulum.controllers.tvlqr.tvlqr

configured tvlqr controller object

time: np.array

time array related to the nominal trajectory

N: int

number of considered knot points

rhof: float

final rho value, from the time-invariant RoA estimation

CHAPTER
SEVENTYNINE

RETURNS

rho_t

[np.array] array that contains the estimated rho value for all the knot points

S: np.array

array that contains the S matrix in each knot point

direct_sphere (d, r_i=0, r_o=1)

Direct Sampling from the d Ball based on Krauth, Werner. Statistical Mechanics: Algorithms and Computations. Oxford Master Series in Physics 13. Oxford: Oxford University Press, 2006. page 42

CHAPTER
EIGHTY

PARAMETERS

d

[int] dimension of the ball

r_i

[int, optional] inner radius, by default 0

r_o

[int, optional] outer radius, by default 1

CHAPTER
EIGHTYONE

RETURNS

np.array

random vector directly sampled from the solid d Ball

sample_from_ellipsoid($M, rho, r_i=0, r_o=1$)

sample directly from the ellipsoid defined by $x^T M x$.

CHAPTER
EIGHTYTWO

PARAMETERS

M

[np.array] Matrix M such that $x^T M x \leq \rho$ defines the hyperellipsoid to sample from

rho

[float] rho such that $x^T M x \leq \rho$ defines the hyperellipsoid to sample from

r_i

[int, optional] inner radius, by default 0

r_o

[int, optional] outer radius, by default 1

CHAPTER
EIGHTYTHREE

RETURNS

np.array

random vector from within the hyperellipsoid

quad_form (M, x)

Helper function to compute quadratic forms such as $x^T M x$

projectedEllipseFromCostToGo (s0Idx, s1Idx, rho, M)

Returns ellipses in the plane defined by the states matching the indices s0Idx and s1Idx for funnel plotting.

getEllipseContour (S, rho, xg)

Returns a certain number(nSamples) of sampled states from the contour of a given ellipse.

CHAPTER EIGHTYFOUR

PARAMETERS

S

[np.array] Matrix S that define one ellipse

rho

[np.array] rho value that define one ellipse

xg

[np.array] center of the ellipse

CHAPTER
EIGHTYFIVE

RETURNS

c

[np.array] random vector of states from the contour of the ellipse

TVrhoSearch (*pendulum, controller, knot, time, h_map, rho_t*)

V step of the bilinear alternationturn used in the SOS funnel estimation.

CHAPTER
EIGHTYSIX

PARAMETERS

pendulum: simple_pendulum.model.pendulum_plant
configured pendulum plant object

controller: simple_pendulum.controllers.tvlqr.tvlqr
configured tvlqr controller object

knot: int
number of considered knot point

time: np.array
time array related to the nominal trajectory

h_map: Dict[pydrake.symbolic.Monomial, pydrake.symbolic.Expression]
map of the coefficients of the multiplier obtained from the multiplier step

rho_t: np.array
array that contains the evolving estimation of the rho values for each knot point

CHAPTER
EIGHTYSEVEN

RETURNS

fail

[boolean] gives info about the correctness of the optimization problem

rho_opt: float

optimized rho value for this knot point

TVmultSearch (*pendulum, controller, knot, time, rho_t*)

Multiplier step of the bilinear alternationturn used in the SOS funnel estimation.

CHAPTER
EIGHTYEIGHT

PARAMETERS

pendulum: simple_pendulum.model.pendulum_plant
configured pendulum plant object

controller: simple_pendulum.controllers.tvlqr.tvlqr
configured tvlqr controller object

knot: int
number of considered knot point

time: np.array
time array related to the nominal trajectory

rho_t: np.array
array that contains the evolving estimation of the rho values for each knot point

CHAPTER
EIGHTYNINE

RETURNS

fail

[boolean] gives info about the correctness of the optimization problem

h_map: Dict[pydrake.symbolic.Monomial, pydrake.symbolic.Expression]

map of the coefficients of the multiplier obtained from the multiplier step

eps: float

optimal cost of the optimization problem that can be useful in the V step

CHAPTER
NINETY

MODEL

CHAPTER
NINETYONE

PARAMETERS

get_params (*params_path*)

Retrieve parameters from a yaml file with name *params_path*

class Environment

Bases: object

Environmental parameters

class Robot

Bases: object

Robot parameters

class Joints

Bases: object

Joint parameters

class Links

Bases: object

Link parameters

calc_m_l (*mass*, *mass_p*)

calc_length_com (*mass_p*, *mass_l*, *length*)

calc_inertia (*mass_p*, *mass_l*, *length*)

calc_inertia_com (*mass_p*, *mass_l*, *length*)

class Actuators

Bases: object

Motor parameters

calc_k_m (*k_t*, *resist*)

calc_k_v (*v_per_hz*)

calc_k_e(k_v)

calc_k_t_from_k_m(k_m , resist)

calc_k_t_from_k_v(k_v)

CHAPTER NINETYTWO

PENDULUM PLANT

```
class PendulumPlant (mass=1.0, length=0.5, damping=0.1, gravity=9.81, coulomb_fric=0.0,  
inertia=None, torque_limit=inf)
```

Bases: object

The PendulumPlant class contains the kinematics and dynamics of the simple pendulum.

The state of the pendulum in this class is described by

state = [angle, angular velocity] (array like with len(state)=2) in units: rad and rad/s

The zero state of the angle corresponds to the pendulum hanging down. The plant expects an actuation input (tau) either as float or array like in units Nm. (in which case the first entry is used (which should be a float))

CHAPTER
NINETYTHREE

PARAMETERS

mass

[float, default=1.0] pendulum mass, unit: kg

length

[float, default=0.5] pendulum length, unit: m

damping

[float, default=0.1] damping factor (proportional to velocity), unit: kg*m/s

gravity

[float, default=9.81] gravity (positive direction points down), unit: m/s²

coulomb_fric

[float, default=0.0] friction term, (independent of magnitude of velocity), unit: Nm

inertia

[float, default=None] inertia of the pendulum (defaults to point mass inertia) unit: kg*m²

torque_limit: float, default=np.inf

maximum torque that the motor can apply, unit: Nm

load_params_from_file (filepath)

Load the pendulum parameters from a yaml file.

93.1 Parameters

filepath

[string] path to yaml file

forward_kinematics (pos)

Computes the forward kinematics.

93.2 Parameters

pos : float, angle of the pendulum

93.3 Returns

list

[A list containing one list (for one end-effector)] The inner list contains the x and y coordinates for the end-effector of the pendulum

inverse_kinematics (ee_pos)

Computes inverse kinematics

93.4 Parameters

ee_pos

[array like,] len(state)=2 contains the x and y position of the end_effector floats, units: m

93.5 Returns

pos

[float] angle of the pendulum, unit: rad

forward_dynamics (state, tau)

Computes forward dynamics

93.6 Parameters

state

[array like] len(state)=2 The state of the pendulum [angle, angular velocity] floats, units: rad, rad/s

tau

[float] motor torque, unit: Nm

93.7 Returns

- float, angular acceleration, unit: rad/s²

inverse_dynamics (*state, accn*)

Computes inverse dynamics

93.8 Parameters

state

[array like] len(state)=2 The state of the pendulum [angle, angular velocity] floats, units: rad, rad/s

accn

[float] angular acceleration, unit: rad/s²

93.9 Returns

tau

[float] motor torque, unit: Nm

rhs (*t, state, tau*)

Computes the integrand of the equations of motion.

93.10 Parameters

t

[float] time, not used (the dynamics of the pendulum are time independent)

state

[array like] len(state)=2 The state of the pendulum [angle, angular velocity] floats, units: rad, rad/s

tau

[float or array like] motor torque, unit: Nm

93.11 Returns

res

[array like] the integrand, contains [angular velocity, angular acceleration]

potential_energy (*state*)

kinetic_energy (*state*)

total_energy (*state*)

CHAPTER

NINETYFOUR

UNIT TESTS

```
class Test (methodName='runTest')
```

Bases: TestCase

Create an instance of the class that will use the named test method when executed. Raises a ValueError if the instance does not have a method with the specified name.

```
MASSES = [0.01, 0.1, 1.0, 10.0, 100.0]
```

```
LENGTHS = [0.01, 0.1, 1.0, 10.0, 100.0]
```

```
DAMPINGS = [0.0, 0.01, 0.1, 1.0]
```

```
GRAVITY = [0.0, 9.81]
```

```
CFRICS = [0.0, 0.01, 0.1, 1.0]
```

```
TLIMITS = [1.0, 2.0, 3.0, 5.0, inf]
```

```
iterations = 10
```

```
epsilon = 0.0001
```

```
max_angle = 5.0
```

```
max_vel = 5.0
```

```
max_tau = 5.0
```

```
test_0_kinematics()
```

Unit test for pendulum kinematics

```
test_1_dynamics()
```

Unit test for pendulum dynamics

CHAPTER
NINETYFIVE

REINFORCEMENT LEARNING

CHAPTER
NINETYSIX

DEEP DETERMINISTIC POLICY GRADIENT (DDPG) TRAINING

CHAPTER
NINETYSEVEN

AGENT

```
class Agent (state_shape, n_actions, action_limits, discount, actor_lr, critic_lr, actor_model, critic_model,  
    target_actor_model, target_critic_model, tau=0.005)
```

Bases: `object`

`prep_state` (*state*)

`get_action` (*state*, *noise_object*=*None*)

`scale_action` (*action*, *mini*, *maxi*)

`train_on` (*batch*)

`update_target_weights` (*tau*=*None*)

`save_model` (*path*)

`load_model` (*path*)

CHAPTER
NINETYEIGHT

DDPG TRAINER

```
class ddpg_trainer(batch_size, validate_every=None, validation_reps=None, train_every_steps=inf)
```

Bases: object

```
init_pendulum(mass=0.57288, length=0.5, inertia=None, damping=0.15, coulomb_friction=0.0,  
              gravity=9.81, torque_limit=2.0)
```

Initialize the pendulum parameters.

CHAPTER
NINETYNINE

PARAMETERS

mass

[float, default=0.57288] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

inertia

[float, default=None] inertia of the pendulum [kg m²] defaults to point mass inertia (mass*length²)

damping

[float, default=0.15] damping factor of the pendulum [kg m/s]

coulomb_friction

[float, default=0.0] coulomb friction of the pendulum [Nm]

gravity

[float, default=9.81] gravity (positive direction points down) [m/s²]

torque_limit

[float, default=2.0] the torque_limit of the pendulum actuator

init_environment (*dt*=0.01, *integrator*='runge_kutta', *max_steps*=1000,
reward_type='open_ai_gym', *state_representation*=2, *validation_limit*=-150,
target=[3.141592653589793, 0.0], *state_target_epsilon*=[0.01, 0.01],
scale_action=True, *random_init*='everywhere')

Initialize the training environment. This includes the simulation parameters of the pendulum.

CHAPTER

PARAMETER

dt

[float, default=0.01] time step [s]

integrator: string

integration method to be used “euler” for euler integrator, “runge_kutta” for Runge-Kutta integrator

max_steps

[int, default=1000] maximum number of timesteps for one training episode i.e. One episode lasts at most max_stepd*dt seconds

reward_type

[string, default=soft_binary_with_repellor] string which defines the reward function options are: ‘continuous’, ‘discrete’, ‘soft_binary’,
‘soft_binary_with_repellor’

state_representation

[int, default=2] determines how the state space of the pendulum is represented state_representation=2 means state = [position, velocity] state_representation=3 means state = [cos(position), sin(position), velocity]

target

[array-like, default=[np.pi, 0.0]] The target state of the pendulum

state_target_epsilon

[array-like, default=[1e-2, 1e-2]] In this vicinity the target counts as reached.

scale_action

[bool, default=True] whether to scale the output of the model with the torque limit of the simulator’s plant. If True the model is expected so return values in the intervall [-1, 1] as action.

init_agent (*replay_buffer_size*=50000, *actor*=None, *critic*=None, *discount*=0.99, *actor_lr*=0.0005, *critic_lr*=0.001, *tau*=0.005)

train (*n_episodes*, *verbose*=True)

save (*path*)

load (*path*)

CHAPTER
ONE

MODELS

`get_actor` (*state_shape*, *upper_bound*=*2.0*, *verbose*=*False*)

`get_critic` (*state_shape*, *n_actions*, *verbose*=*False*)

CHAPTER
TWO

NOISE

```
class OUActionNoise (mean, std_deviation, theta=0.15, dt=0.01, x_initial=None)
Bases: object
    reset()
```

CHAPTER THREE

REPLAY BUFFER

```
class ReplayBuffer(max_size, num_states, num_actions)
```

Bases: object

Replay buffer class to store experiences for a reinforcement learning agent.

CHAPTER FOUR

PARAMETERS

max_size: int

maximum number of experiences to store in the replay buffer. When adding experiences beyond this limit, the first entry is deleted.

num_state: int

the dimension of the state space

num_actions: int

the dimension of the action space

append (*obs_tuple*)

Add an experience to the replay buffer. When adding experiences beyond the max_size limit, the first entry is deleted. An observation consists of (state, action, next_state, reward, done)

104.1 Parameters

obs_tuple: array-like

an observation (s,a,s',r,d) to store in the buffer

sample_batch (*batch_size*)

Sample a batch from the replay buffer.

104.2 Parameters

batch_size: int

number of samples in the returned batch

104.3 Returns

tuple

(s_batch,a_batch,s'_batch,r_batch,d_batch) a tuple of batches of state, action, reward, next_state, done

clear()

Clear the Replay Buffer.

CHAPTER
FIVE

SOFT ACTOR CRITIC (SAC) TRAINING

CHAPTER
SIX

SAC TRAINER

```
class sac_trainer(log_dir='sac_training')
```

Bases: object

Class to train a policy for pendulum swingup with the state actor critic (sac) method.

CHAPTER SEVEN

PARAMETER

log_dir

[string, default="sac_training"] path to directory where results and log data will be stored

init_pendulum (*mass*=0.57288, *length*=0.5, *inertia*=None, *damping*=0.15, *coulomb_friction*=0.0, *gravity*=9.81, *torque_limit*=2.0)

Initialize the pendulum parameters.

107.1 Parameters

mass

[float, default=0.57288] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

inertia

[float, default=None] inertia of the pendulum [kg m²] defaults to point mass inertia (mass*length²)

damping

[float, default=0.15] damping factor of the pendulum [kg m/s]

coulomb_friction

[float, default=0.0] coulomb friction of the pendulum [Nm]

gravity

[float, default=9.81] gravity (positive direction points down) [m/s²]

torque_limit

[float, default=2.0] the torque_limit of the pendulum actuator

init_environment (*dt*=0.01, *integrator*='runge_kutta', *max_steps*=1000, *reward_type*='soft_binary_with_repellor', *state_representation*=2, *validation_limit*=-150, *target*=[3.141592653589793, 0.0], *state_target_epsilon*=[0.01, 0.01], *random_init*='everywhere')

Initialize the training environment. This includes the simulation parameters of the pendulum.

107.2 Parameter

dt

[float, default=0.01] time step [s]

integrator: string

integration method to be used “euler” for euler integrator, “runge_kutta” for Runge-Kutta integrator

max_steps

[int, default=1000] maximum number of timesteps for one training episode i.e. One episode lasts at most max_stepd*dt seconds

reward_type

[string, default=soft_binary_with_repellor] string which defines the reward function options are: ‘continuous’, ‘discrete’, ‘soft_binary’,

‘soft_binary_with_repellor’

state_representation

[int, default=2] determines how the state space of the pendulum is represented state_representation=2 means state = [position, velocity] state_representation=3 means state = [cos(position), sin(position), velocity]

target

[array-like, default=[np.pi, 0.0]] The target state of the pendulum

state_target_epsilon

[array-like, default=[1e-2, 1e-2]] In this vicinity the target counts as reached.

init_agent (learning_rate=0.0003, warm_start=False, warm_start_path='', verbose=1)

Initilize the agent.

107.3 Parameters

learning_rate

[float, default=0.0003] learning rate of the agent

warm_start

[bool, default=False] whether to use a pretrained model as initial model for training

warm_start_path

[string, default=""] path to the model to load for warm start if warm_start==True

verbose

[int, default=1] enable/disable printing of training progression to terminal

train(*training_timesteps*=1000000.0, *reward_threshold*=1000.0, *eval_frequency*=10000, *n_eval_episodes*=20, *verbose*=1)

Train the agent and save the model. The model will be saved to os.path.join(self.logdir, “best_model”).

107.4 Parameter

training_timesteps

[int, default=1e6] total number of training steps. After training_steps steps the training terminates

reward_threshold

[float, default=1000.0] If the evaluation of the agent surpasses this reward_threshold the training terminates early

n_eval_episodes

[int, default=20] number of episodes used during evaluation

verbose

[int, default=1] enable/disable printing of training progression to terminal

**CHAPTER
EIGHT**

SIMULATION

CHAPTER
NINE

GYM ENVIRONMENT

```
class SimplePendulumEnv(simulator, max_steps=5000, target=[3.141592653589793, 0.0],  
                        state_target_epsilon=[0.01, 0.01], reward_type='continuous', dt=0.001,  
                        integrator='runge_kutta', state_representation=2, validation_limit=-150,  
                        scale_action=True, random_init='False')
```

Bases: Env

An environment for reinforcement learning.

CHAPTER

PARAMETERS

simulator : simulator object **max_steps** : int, default=5000

maximum steps the agent can take before the episode is terminated

target

[array-like, default=[np.pi, 0.0]] the target state of the pendulum

state_target_epsilon: array-like, default=[1e-2, 1e-2]

target epsilon for discrete reward type

reward_type

[string, default='continuous'] the reward type selects the reward function which is used options are:
'continuous', 'discrete', 'soft_binary',

'soft_binary_with_repellor', 'open_ai_gym'

dt

[float, default=1e-3] timestep for the simulation

integrator

[string, default='runge_kutta'] the integrator which is used by the simulator options : 'euler',
'runge_kutta'

state_representation

[int, default=2] determines how the state space of the pendulum is represented 2 means state = [position, velocity] 3 means state = [cos(position), sin(position), velocity]

validation_limit

[float, default=-150] If the reward during validation episodes surpasses this value the training stops early

scale_action

[bool, default=True] whether to scale the output of the model with the torque limit of the simulator's plant. If True the model is expected to return values in the interval [-1, 1] as action.

random_init

[string, default="False"] A string determining the random state initialisation "False" : The pendulum is set to [0, 0], "start_vicinity" : The pendulum position and velocity

are set in the range [-0.31, -0.31],

"everywhere"

[The pendulum is set to a random state in the whole] possible state space

step (*action*)

Take a step in the environment.

110.1 Parameters

action

[float] the torque that is applied to the pendulum

110.2 Returns

observation

[array-like] the observation from the environment after the step

reward

[float] the reward received on this step

done

[bool] whether the episode has terminated

info

[dictionary] may contain additional information (empty at the moment)

reset (*state=None, random_init='start_vicinity'*)

Reset the environment. The pendulum is initialized with a random state in the vicinity of the stable fixpoint (position and velocity are in the range[-0.31, 0.31])

110.3 Parameters

state

[array-like, default=None] the state to which the environment is reset if state==None it defaults to the random initialisation

random_init

[string, default=None] A string determining the random state initialisation if None, defaults to self.random_init “False” : The pendulum is set to [0, 0], “start_vicinity” : The pendulum position and velocity

are set in the range [-0.31, -0.31],

“everywhere”

[The pendulum is set to a random state in the whole] possible state space

110.4 Returns

observation

[array-like] the state the pendulum has been initialized to

110.5 Raises:

NotImplementedError

when state==None and random_init does not indicate one of the implemented initializations

render (mode='human')

Renders the environment.

The set of supported modes varies per environment. (And some environments do not support rendering at all.) By convention, if mode is:

- human: render to the current display or terminal and return nothing. Usually for human consumption.
- rgb_array: Return an numpy.ndarray with shape (x, y, 3), representing RGB values for an x-by-y pixel image, suitable for turning into a video.
- ansi: Return a string (str) or StringIO.StringIO containing a terminal-style text representation. The text can include newlines and ANSI escape sequences (e.g. for colors).

Note:

Make sure that your class's metadata 'render.modes' key includes

the list of supported modes. It's recommended to call super() in implementations to use the functionality of this method.

Args:

mode (str): the mode to render with

Example:

```
class MyEnv(Env):
    metadata = {'render.modes': ['human', 'rgb_array']}
    def render(self, mode='human'):
        if mode == 'rgb_array':
            return np.array(...) # return RGB frame suitable for video
        elif mode == 'human':
            ... # pop up a window and render
        else:
            super(MyEnv, self).render(mode=mode) # just raise an exception
```

close()

Override close in your subclass to perform any necessary cleanup.

Environments will automatically close() themselves when garbage collected or when the program exits.

get_observation(state)

Transform the state from the simulator an observation by wrapping the position to the observation space. If state_representation==3 also transforms the state to the trigonometric value form.

110.6 Parameters

state

[array-like] state as output by the simulator

110.7 Returns

observation

[array-like] observation in environment format

get_state_from_observation(obs)

Transform the observation to a pendulum state. Does nothing for state_representation==2. If state_representation==3 transforms trigonometric form back to regular form.

110.8 Parameters

obs

[array-like] observation as received from get_observation

110.9 Returns

state

[array-like] state in simulator form

swingup_reward(observation, action)

Calculate the reward for the pendulum for swinging up to the instable fixpoint. The reward function is selected based on the reward type defined during the object initialization.

110.10 Parameters

state

[array-like] the observation that has been received from the environment

110.11 Returns

reward

[float] the reward for swinging up

110.12 Raises

NotImplementedError

when the requested reward_type is not implemented

check_final_condition()

Checks whether a terminating condition has been met. The only terminating condition for the pendulum is if the maximum number of steps has been reached.

110.13 Returns

done

[bool] whether a terminating condition has been met

is_goal(obs)

Checks whether an observation is in the goal region. The goal region is specified by the target and state_target_epsilon parameters in the class initialization.

110.14 Parameters

obs

[array-like] observation as received from get_observation

110.15 Returns

goal

[bool] whether to observation is in the goal region

validation_criterion (*validation_rewards*, *final_obs=None*, *criterion=None*)

Checks whether a list of rewards and optionally final observations fulfill the validation criterion. The validation criterion is fulfilled if the mean of the validation_rewards is greater than criterion. If final obs is also given, at least 90% of the observations have to be in the goal region.

110.16 Parameters

validation_rewards

[array-like] A list of rewards (floats).

final_obs

[array-like, default=None] A list of final observations. If None final observations are not considered.

criterion: float, default=None

The reward limit which has to be surpassed.

110.17 Returns

passed

[bool] Whether the rewards pass the validation test

CHAPTER
ONE

SIMULATOR

```
class Simulator(plant)
Bases: object
Simulator class, can simulate and animate the pendulum
```

CHAPTER TWO

PARAMETERS

plant: plant object

(e.g. PendulumPlant from simple_pendulum.models.pendulum_plant.py)

set_state (*time, x*)

set the state of the pendulum plant

112.1 Parameters

time: float

time, unit: s

x: type as self.plant expects a state,

state of the pendulum plant

get_state ()

Get current state of the plant

112.2 Returns

self.t

[float,] time, unit: s

self.x

[type as self.plant expects a state] plant state

reset_data_recorder ()

Reset the internal data recorder of the simulator

record_data (*time, x, tau*)

Records data in the internal data recorder

112.3 Parameters

time

[float] time to be recorded, unit: s

x

[type as self.plant expects a state] state to be recorded, units: rad, rad/s

tau

[type as self.plant expects an actuation] torque to be recorded, unit: Nm

euler_integrator (*t, y, tau*)

Euler integrator for the simulated plant

112.4 Parameters

t

[float] time, unit: s

y: type as self.plant expects a state

state of the pendulum

tau: type as self.plant expects an actuation

torque input

112.5 Returns

array-like : the Euler integrand

runge_integrator (*t, y, dt, tau*)

Runge-Kutta integrator for the simulated plant

112.6 Parameters

t

[float] time, unit: s

y: type as self.plant expects a state

state of the pendulum

dt: float

time step, unit: s

tau: type as self.plant expects an actuation

torque input

112.7 Returns

array-like : the Runge-Kutta integrand

step (*tau*, *dt*, *integrator='runge_kutta'*)

Performs a single step of the plant.

112.8 Parameters

tau: type as self.plant expects an actuation
torque input

dt: float
time step, unit: s

integrator: string
“euler” for euler integrator “runge_kutta” for Runge-Kutta integrator

simulate (*t0*, *x0*, *tf*, *dt*, *controller=None*, *integrator='runge_kutta'*)

Simulates the plant over a period of time.

112.9 Parameters

t0: float
start time, unit s

x0: type as self.plant expects a state
start state

tf: float
final time, unit: s

controller: A controller object of the type of the
AbstractController in simple_pendulum.controllers.abstract_controller.py If None, a free pen-
dulum is simulated.

integrator: string
“euler” for euler integrator, “runge_kutta” for Runge-Kutta integrator

112.10 Returns

self.t_values

[list] a list of time values

self.x_values

[list] a list of states

self.tau_values

[list] a list of torques

```
simulate_and_animate(t0, x0, tf, dt, controller=None, integrator='runge_kutta', phase_plot=False,  
save_video=False, video_name='video')
```

Simulation and animation of the plant motion. The animation is only implemented for 2d serial chains.
input: Simulates the plant over a period of time.

112.11 Parameters

t0: float

start time, unit s

x0: type as self.plant expects a state

start state

tf: float

final time, unit: s

controller: A controller object of the type of the

AbstractController in simple_pendulum.controllers.abstract_controller.py If None, a free pendulum is simulated.

integrator: string

“euler” for euler integrator, “runge_kutta” for Runge-Kutta integrator

phase_plot: bool

whether to show a plot of the phase space together with the animation

save_video: bool

whether to save the animation as mp4 video

video_name: string

if save_video, the name of the file where the video will be stored

112.12 Returns

self.t_values

[list] a list of time values

self.x_values

[list] a list of states

self.tau_values

[list] a list of torques

get_arrow (*radius, centX, centY, angle_, theta2_, color_=black*)

set_arrow_properties (*arc, head, tau, x, y*)

CHAPTER THREE

TRAJECTORY OPTIMIZATION

CHAPTER
FOUR

DDP

CHAPTER
FIVE

DIRECT COLLOCATION

CHAPTER
SIX

DIRECT COLLOCATION CALCULATOR

```
class DirectCollocationCalculator
```

Bases: object

Class to calculate a control trajectory with direct collocation.

```
init_pendulum(mass=0.57288, length=0.5, damping=0.15, gravity=9.81, torque_limit=2.0)
```

Initialize the pendulum parameters.

CHAPTER SEVEN

PARAMETERS

mass

[float, default=0.57288] mass of the pendulum [kg]

length

[float, default=0.5] length of the pendulum [m]

damping

[float, default=0.15] damping factor of the pendulum [kg m/s]

gravity

[float, default=9.81] gravity (positive direction points down) [m/s²]

torque_limit

[float, default=2.0] the torque_limit of the pendulum actuator

compute_trajectory (*N*=21, *max_dt*=0.5, *start_state*=[0.0, 0.0],
goal_state=[3.141592653589793, 0.0], *initial_x_trajectory*=None)

Compute a trajectory from a start state to a goal state for the pendulum.

CHAPTER
EIGHT

PARAMETERS

N

[int, default=21] number of collocation points

max_dt

[float, default=0.5] maximum allowed timestep between collocation points

start_state

[array_like, default=[0.0, 0.0]] the start state of the pendulum [position, velocity]

goal_state

[array_like, default=[np.pi, 0.0]] the goal state for the trajectory

initial_x_trajectory

[array-like, default=None] initial guess for the state space trajectory ignored if None

CHAPTER
NINE

RETURNS

x_trajectory

[pydrake.trajectories.PiecewisePolynomial] trajectory in state space

dircol

[pydrake.systems.trajectory_optimization.DirectCollocation] DirectCollocation pydrake object

result

[pydrake.solvers.mathematicalprogram.MathematicalProgramResult] MathematicalProgramResult pydrake object

plot_phase_space_trajectory (*x_trajectory*, *save_to=None*)

Plot the computed trajectory in phase space.

CHAPTER

PARAMETERS

x_trajectory

[pydrake.trajectories.PiecewisePolynomial] the trajectory returned from the compute_trajectory function.

save_to

[string, default=None] string pointing to the location where the figure is supposed to be stored. If save_to==None, the figure is not stored but shown in a window instead.

extract_trajectory (*x_trajectory, dircol, result, N=801*)

Extract time, position, velocity and control trajectories from the outputs of the compute_trajectory function.

CHAPTER ONE

PARAMETERS

x_trajectory

[pydrake.trajectories.PiecewisePolynomial] trajectory in state space

dircol

[pydrake.systems.trajectory_optimization.DirectCollocation] DirectCollocation pydrake object

result

[pydrake.solvers.mathematicalprogram.MathematicalProgramResult] MathematicalProgramResult pydrake object

N

[int, default=801] The number of sampling points of the returned trajectories

CHAPTER
TWO

RETURNS

time_traj

[array_like] the time trajectory

theta

[array_like] the position trajectory

theta_dot

[array_like] the velocity trajectory

torque_traj

[array_like] the control (torque) trajectory

CHAPTER THREE

UNIT TESTS

```
class Test (methodName='runTest')
```

Bases: TestCase

Create an instance of the class that will use the named test method when executed. Raises a ValueError if the instance does not have a method with the specified name.

```
epsilon = 0.2
```

```
test_0_direct_collocation()
```

CHAPTER
FOUR

ILQR

CHAPTER
FIVE

ILQR CALCULATOR

Large parts taken from [Russ Tedrake](#).

```
class iLQR_Calculator(n_x=2, n_u=1)
```

Bases: object

Class to calculate an optimal trajectory with an iterative linear quadratic regulator (iLQR). This implementation uses the pydrake symbolic library.

CHAPTER
SIX

PARAMETERS

n_x

[int, default=2] The size of the state space.

n_u

[int, default=1] The size of the control space.

set_start (x0)

Set the start state for the trajectory.

126.1 Parameters

x0

[array-like] the start state. Should have the shape of (n_x,)

set_discrete_dynamics (dynamics_func)

Sets the dynamics function for the iLQR calculation.

126.2 Parameters

dynamics_func

[function] dynamics_func should be a function with inputs (x, u) and output xd

set_stage_cost (stage_cost_func)

Set the stage cost (running cost) for the ilqr optimization.

126.3 Parameters

stage_cost_func

[function] stage_cost_func should be a function with inputs (x, u) and output cost

set_final_cost (final_cost_func)

Set the final cost for the ilqr optimization.

126.4 Parameters

final_cost_func

[function] final_cost_func should be a function with inputs x and output cost

init_derivatives ()

Initialize the derivatives of the dynamics.

run_ilqr (N=50, init_u_trj=None, init_x_trj=None, shift=False, max_iter=50, break_cost_redu=1e-06, regu_init=100)

Run the iLQR optimization and receive a optimal trajectory for the defined cost function.

126.5 Parameters

N

[int, default=50] The number of waypoints for the trajectory

init_u_trj

[array-like, default=None] initial guess for the control trajectory ignored if None

init_x_trj

[array_like, default=None] initial guess for the state space trajectory ignored if None

shift

[bool, default=False] whether to shift the initial guess trajectories by one entry (delete the first entry and duplicate the last entry)

max_iter

[int, default=50] optimization iterations the algorith makes at every timestep

break_cost_redu

[float, default=1e-6] cost at which the optimization breaks off early

regu_init

[float, default=100] initialization value for the regularizer

126.6 Returns

x_trj

[array-like] state space trajectory

u_trj

[array-like] control trajectory

cost_trace

[array-like] trace of the cost development during the optimization

regu_trace

[array-like] trace of the regularizer development during the optimization

redu_ratio_trace

[array-like]

trace of ratio of cost_reduction and expected cost reduction

 during the optimization

redu_trace

[array-like] trace of the cost reduction development during the optimization

CHAPTER SEVEN

SYMBOLIC

Large parts taken from Russ Tedrake.

```
class iLQR_Calculator(n_x=2, n_u=1)
```

Bases: object

Class to calculate an optimal trajectory with an iterative linear quadratic regulator (iLQR). This implementation uses sympy.

CHAPTER
EIGHT

PARAMETERS

n_x

[int, default=2] The size of the state space.

n_u

[int, default=1] The size of the control space.

set_start (x0)

Set the start state for the trajectory.

128.1 Parameters

x0

[array-like] the start state. Should have the shape of (n_x,)

set_discrete_dynamics (dynamics_func)

Sets the dynamics function for the iLQR calculation.

128.2 Parameters

dynamics_func

[function] dynamics_func should be a function with inputs (x, u) and output xd

rollout (u_trj)

set_stage_cost (stage_cost_func)

Set the stage cost (running cost) for the ilqr optimization.

128.3 Parameters

stage_cost_func

[function] stage_cost_func should be a function with inputs (x, u) and output cost

set_final_cost (final_cost_func)

Set the final cost for the ilqr optimization.

128.4 Parameters

final_cost_func

[function] final_cost_func should be a function with inputs x and output cost

cost_trj (x_trj, u_trj)

init_derivatives ()

Initialize the derivatives of the dynamics.

compute_stage_cost_derivatives (x, u)

compute_final_cost_derivatives (x)

Q_terms (l_x, l_u, l_xx, l_ux, l_uu, f_x, f_u, V_x, V_xx)

gains (Q_uu, Q_u, Q_ux)

V_terms (Q_x, Q_u, Q_xx, Q_ux, Q_uu, K, k)

expected_cost_reduction (Q_u, Q_uu, k)

forward_pass (x_trj, u_trj, k_trj, K_trj)

backward_pass (x_trj, u_trj, regu)

run_ilqr (N=50, init_u_trj=None, init_x_trj=None, shift=False, max_iter=50, break_cost_redu=1e-06, regu_init=100)

Run the iLQR optimization and receive a optimal trajectory for the defined cost function.

128.5 Parameters

N

[int, default=50] The number of waypoints for the trajectory

init_u_trj

[array-like, default=None] initial guess for the control trajectory ignored if None

init_x_trj

[array-like, default=None] initial guess for the state space trajectory ignored if None

shift

[bool, default=False] whether to shift the initial guess trajectories by one entry (delete the first entry and duplicate the last entry)

max_iter

[int, default=50] optimization iterations the algorithm makes at every timestep

break_cost_redu

[float, default=1e-6] cost at which the optimization breaks off early

regu_init

[float, default=100] initialization value for the regularizer

128.6 Returns

x_trj

[array-like] state space trajectory

u_trj

[array-like] control trajectory

cost_trace

[array-like] trace of the cost development during the optimization

regu_trace

[array-like] trace of the regularizer development during the optimization

redu_ratio_trace

[array-like]

trace of ratio of cost_reduction and expected cost reduction

 during the optimization

redu_trace

[array-like] trace of the cost reduction development during the optimization

CHAPTER
NINE

PENDULUM DYNAMICS

check_type (*x*)

checks the type of *x* and returns the suitable library (pydrake.symbolic, sympy or numpy) for furhter cal-
culations on *x*.

pendulum_continuous_dynamics (*x, u, m=0.5, l=0.5, b=0.15, cf=0.0, g=9.81, inertia=0.125*)

pendulum_discrete_dynamics_euler (*x, u, dt, m=0.57288, l=0.5, b=0.15, cf=0.0, g=9.81,
inertia=0.125*)

pendulum_discrete_dynamics_rungekutta (*x, u, dt, m=0.5, l=0.5, b=0.15, cf=0.0, g=9.81,
inertia=0.125*)

pendulum.swingup_stage_cost (*x, u, goal=[3.141592653589793, 0], Cu=10.0, Cp=0.01, Cv=0.01,
Cen=0.0, m=0.5, l=0.5, b=0.15, cf=0.0, g=9.81*)

pendulum.swingup_final_cost (*x, goal=[3.141592653589793, 0], Cp=1000.0, Cv=10.0, Cen=0.0,
m=0.5, l=0.5, b=0.15, cf=0.0, g=9.81*)

pendulum3_discrete_dynamics_euler (*x, u, dt, m=0.5, l=0.5, b=0.15, cf=0.0, g=9.81,
inertia=0.125*)

pendulum3_discrete_dynamics_rungekutta (*x, u, dt, m=0.5, l=0.5, b=0.15, cf=0.0, g=9.81,
inertia=0.125*)

pendulum3.swingup_stage_cost (*x, u, goal=[-1, 0, 0], Cu=10.0, Cp=0.01, Cv=0.01, Cen=0.0,
m=0.5, l=0.5, b=0.15, cf=0.0, g=9.81*)

pendulum3.swingup_final_cost (*x, goal=[-1, 0, 0], Cp=1000.0, Cv=10.0, Cen=0.0, m=0.57288,
l=0.5, b=0.15, cf=0.0, g=9.81*)

CHAPTER

UNIT TESTS

```
class Test(methodName='runTest')
```

Bases: TestCase

Create an instance of the class that will use the named test method when executed. Raises a ValueError if the instance does not have a method with the specified name.

```
epsilon = 0.2

test_0_iLQR_computation_nx2()

test_0_iLQR_computation_nx3()

test_0_iLQR_computation_nx2_sympy()

test_0_iLQR_computation_nx3_sympy()
```

CHAPTER
ONE

UTILITIES

CHAPTER
TWO

PARSING

syntax()

CHAPTER THREE

PERFORMANCE PROFILING

```
motor_send_n_commands (numTimes)  
motor_speed_test (motor_id='0x01', can_port='can0', n=1000)  
profiler (data_dict, start, end, meas_dt)  
validate avg dt of the control loop with (start time - end time) / numSteps
```

CHAPTER
FOUR

PLOTTING

```
swingup(save, output_folder, data_dict)  
grav_comp(args, output_folder, data_dict)  
sys_id_unified(output_folder, meas_time=None, meas_pos=None, meas_vel=None, meas_tau=None,  
    acc=None)  
sys_id_comparison(output_folder, meas_time, vel_dict, tau_dict, acc_dict)  
sys_id_result(output_folder, t, ref_trq, est_trq)
```

CHAPTER
FIVE

DATA PROCESSING

read (*WORK_DIR*, *params_file*, *urdf_file*, *csv_file*)

prepare_empty (*dt*, *tf*)

prepare_trajectory (*csv_path*)

inputs:

csv_path: string

path to a csv file containing a trajectory in the below specified format

The csv file should have 4 columns with values for [time, position, velocity, torque] respectively. The values should be separated with a comma. Each row in the file is one timestep. The number of rows can vary. The values are assumed to be in SI units, i.e. time in s, position in rad, velocity in rad/s, torque in Nm. The first line in the csv file is reserved for comments and will be skipped during read out.

Example:

time, position, velocity, torque 0.00, 0.00, 0.00, 0.10 0.01, 0.01, 0.01, -0.20 0.02,

cut (*data_measured*, *data_desired*)

save (*output_folder*, *data_dict*)

saveFunnel (*rho*, *S_t*, *time*, *max_dt*, *N*, *estMethod*=")

getEllipseFromCsv (*csv_path*, *index*)

CHAPTER
SIX

UNITS

`rad_to_deg(theta_rad)`

`deg_to_rad(theta_deg)`

CHAPTER
SEVEN

FILTERS

CHAPTER
EIGHT

FAST FOURIER TRANSFORM

fast_fourier_transform(*data_measured*, *data_desired*, *n*, *t*)

Fast Fourier transform method

scipy_fft(*data_measured*, *smooth_freq*=100)

SciPy alternative

CHAPTER
NINE

LOW-PASS

online_filter (*data_measured*, *n*, *alpha*)

CHAPTER

MOVING AVERAGE

```
data_filter(x, N)
data_filter_realtime_1(data_measured_list, data_measured, window=10)
data_filter_realtime_2(i, data_measured_list, window=10)
```

CHAPTER
ONE

SAVITZKY-GOLAY

`savitzky_golay_filter`(*data_measured*, *window*, *degree*)

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