Institute for Aerospace Studies
UNIVERSITY OF TORONTO

LABORATORY 3

Monocular Feature Detection and Mapping

ROB521 Autonomous Mobile Robotics Winter 2020

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1 Introduction

This is the third laboratory exercise of ROB521—Autonomous Mobile Robotics. The course will encompass a total of four labs and a design project, all of which are to be completed inthe scheduled practicum periods. Each of the four labs will grow in complexity and intended to demonstrate important robotic concepts presented during the lectures. Our robot of choice: *Turtlebot 3 Waffle Pi* running the operating system *ROS*.

You will be required to hand in a brief lab report and will be graded on this lab.

2 Objective

The objective of this lab is to develop a map of visual features while estimating the robot's pose. In particular, you are

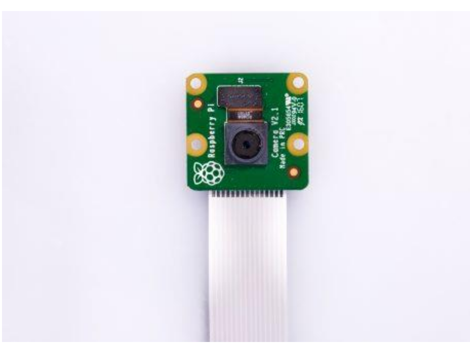
- *To learn about calibrating and using the robot's camera*
- *To extract and track features in the image plane*
- *To estimate the position of landmarks in 3D from monocular image measurements and wheel odometry based robot poses.*

3 Getting Started

3.1 Remote Control of a Robot

You will again use remote control of the robot for motion through the environment. Refer to Lab's 1 and 2 for the details if necessary.

3.2 Accessing Camera Data



The Raspberry Pi Camera Module v2 replaced the original Camera Module in April 2016. The v2 Camera Module has a Sony IMX219 8-megapixel sensor (compared to the 5-megapixel OmniVision OV5647 sensor of the original camera). The Camera Module can be used to take high-definition video, as well as stills photographs. It's easy to use for beginners, but has plenty to offer advanced users if you're looking to expand your knowledge. You can also use the libraries we bundle with the camera to create effects. Detailed specifications are available : http://emanual.robotis.com/docs/en/platform/turtlebot3/appendix_raspi_cam/

To load full robot including lidar, and all other sensors except the camera, run the following command on the robot (remember to ssh in first):

```
$ roslaunch turtlebot3_bringup turtlebot3_robot.launch
```

To just load the camera, again on the robot:

```
$ roslaunch turtlebot3_bringup turtlebot3_rpicamera.launch
```

To view the image data, open rviz and add the image visualization (under "By Topic"):

```
$ rviz rviz
```

To dynamically change camera settings such as exposure, try:

```
$ rosrun rqt_reconfigure rqt_reconfigure
```

3.3 Working with OpenCV

The OpenCV library is a well established package with excellent integration in ROS. It is extremely convenient for experimenting with a wide range of computer vision methods, and is both well documented and accessible in Python for ease of use. We'll be using the Feature2D library in OpenCV, whose documentation can be found here: https://docs.opencv.org/master/da/d9b/group__features2d.html.

There are many interesting tutorials that cover all kinds of applications of OpenCV to computer vision problems.
https://docs.opencv.org/master/d9/df8/tutorial_root.html

Specific tutorials that are useful to try when first learning OpenCV
Changing Contrast and Brightness:
https://docs.opencv.org/master/d3/dc1/tutorial_basic_linear_transform.html

Canny edge detector:
https://docs.opencv.org/master/da/d5c/tutorial_canny_detector.html

We will work with feature extraction, description and matching methods, for which there are a plethora of options. For some interesting tutorials on using these methods, see here:
https://docs.opencv.org/master/d9/d97/tutorial_table_of_content_features2d.html

4 Assignment

4.1 Task 1: Calibrate the camera

Once again, we start the lab with a calibration exercise. This time, you will perform a basic camera calibration using the checkerboard target and predefined calibration routines available with the Turtlebot3. Although all the heavy lifting is done for you, you will need to carefully work through the calibration procedure and present your calibration values and answer some questions in the final report for this lab.

The raspicam_node package contains a calibration file for the raspberry PI camera versions 1 and 2. However, we will generate our own for our camera using the camera_calibration package from ROS.

1) If you haven't done so already, load the camera by running the following command on the robot:

```
$ roslaunch turtlebot3_bringup turtlebot3_rpicamera.launch
```

2) Check that the camera image message is publishing and is visible on the desktop, using rostopic list.

3) Launch the monocular camera calibration tool on the desktop using the following command:

```
$ rosrun camera_calibration cameracalibrator.py --size 8x6 --square 0.0255 image:=/raspicam_node/image camera:=/raspicam_node --no-service-check
```

The target is actually 9x7 checkerboards, but as you can see in the figure below, the ROS camera_calibration package only uses the inner 8x6 grid. The parameter 0.0255 is the length of the checkerboard square for your calibration targets, which was measured to be 25.5 mm. Do check this value if you have a ruler with you. The image and camera arguments must match what is visible in your ros topics.

4) To perform the calibration, move the checkerboard throughout the visible region. The GUI that loads (eventually) has bars for x, y, size and skew variation and you must excite the full range of each of these modes to get a good calibration. A common procedure is to start in the center of the image parallel to the image plane and move forward until the target is detected and takes about half the image. Then move around the edges of the visible region to cover x and y variation. Next move forward and back to the limits of the checkerboard detection range to complete the size variation. Finally move left to right and up and down with different extreme skews, and be sure to tilt the target vertically and horizontally. When all the bars have turned green, the calibrate circle with turn a dark green and you are ready to calibrate.

5) Press calibrate (nothing happens for while), and then press save and commit. Save will store the calibration to /tmp/calibrationdata.tar.gz. After the calibration is complete you will see the calibration results in the terminal and the calibrated image in the calibration window. A successful calibration will result in real-world straight edges appearing straight in the corrected image. A failed calibration usually results in blank or unrecognizable images, or images that do not preserve straight edges.

6) After a successful calibration, you can use the slider at the top of the calibration window to change the size of the rectified image. A scale of

0.0 means that the image is sized so that all pixels in the rectified image are valid. The rectified image has no border, but some pixels from the original image are discarded. A scale of 1.0 means that all pixels in the original image are visible, but the rectified image has black borders where there are no input pixels in the original image.

Example terminal output.

```
D =  [-0.33758562758914146, 0.11161239414304096, -0.00021819272592442094, -3.029195446330518e-05]

K =  [430.21554970319971, 0.0, 306.6913434743704, 0.0, 430.53169252696676, 227.22480030078816, 0.0, 0.0, 1.0]

R =  [1.0, 0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 1.0]

P =  [1.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0]

# oST version 5.0 parameters


[image]

width

640


height

480


[narrow_stereo/left]


camera matrix

430.215550 0.000000 306.691343

0.000000 430.531693 227.224800

0.000000 0.000000 1.000000


distortion

-0.337586 0.111612 -0.000218 -0.000030 0.0000


rectification

1.000000 0.000000 0.000000

0.000000 1.000000 0.000000

0.000000 0.000000 1.000000
```

```
projection
1.000000 0.000000 0.000000 0.000000
0.000000 1.000000 0.000000 0.000000
0.0      000 1.000000 0.000000
```

If you are satisfied with the calibration, click COMMIT to send the calibration parameters to the camera for permanent storage. The GUI exits and you should see "writing calibration data to ..." in the console. Commit adds it to ~/.ros/camera_info where it can be loaded automatically during launch.

The intrinsic camera matrix for the raw (distorted) images has the following parameters.

```
     [fx  0 cx]
K = [ 0 fy cy]
     [ 0  0  1]
```

The camera matrix projects 3D points in the camera coordinate frame to 2D pixel coordinates using the focal lengths (fx, fy) and principal point (cx, cy).

The distortion parameters are as follows, with the size depending on the selected distortion model. For the "plumb_bob" model, the 5 parameters are: (k1, k2, t1, t2, k3).

The full tutorial on [Monocular Camera Calibration tutorial]() has additional details if you get stuck, and walks you through the process of how to calibrate a single camera.

To complete this section, present your intrinsic calibration parameters to the TAs. You should save your calibration matrix and distortion parameter estimates to the terminal using print statements and record them for your report and subsequent use in Part 4.3.

Due to new University of Toronto restrictions, you will complete both 4.2 and 4.3 offline using the provided dataset. You can complete them using either python 2 or python 3 on any operating system.

4.2 Task 2: Extract and match features

In this task, you will build a functional front end for monocular visual odometry and SLAM. You will rely on the OpenCV library to extract, describe and match features, perform outlier rejection and experiment with different settings to fine tune your front end. An example for how to do this is provided below, but please experiment with the options available to you in the features2d package of OpenCV. You will need to use your implementation for part 3 as well, so you can either use the code in **l3_mapping.py** to start, or you can start from scratch.

To get started, we'll follow a simple path through the extract, describe and match paradigm.

1) ~~Start by converting your ROS image to the OpenCV format using CvBridge. Now use your distortion and intrinsic calibration parameters to undistort your image. You can refer to this OpenCV documentation on how to do that: https://opencv-python-tutroals.readthedocs.io/en/latest/py_tutorials/py_calib3d/py_calibration/py_calibration.html#undistortion~~
Removed since half of the students cannot complete.

2) Using the sample code provided, apply Harris corner extraction. First, convert your RGB image to grayscale. Next you will call the appropriate feature extraction method. Finally visualize the results using the provided tools and store a sample image with visualize features for your report. You can refer to this OpenCV documentation on how to do that: https://opencv-python-tutroals.readthedocs.io/en/latest/py_tutorials/py_feature2d/py_features_harris/py_features_harris.html

3) Next, you will compute descriptors using extracted salient features. Note that this is separate from the previous Harris Corner part. In this part, we'll use ORB feature descriptor, but feel free to try other detector/descriptor pairs. You can always refer to OpenCV documentation: https://opencv-python-tutroals.readthedocs.io/en/latest/py_tutorials/py_feature2d/py_orb/py_orb.html

4) Next, you will match the features using the brute force matcher. To do so, we need at least two images to match, and will use the current image and the next image in a typical odometry fashion. You can refer to this OpenCV documentation here for brute force matcher: https://docs.opencv.org/3.4/d3/da1/classcv_1_1BFMatcher.html

5) You will need to display the matches (for a single pair of images). Call the appropriate OpenCV drawMatch function.

4.3 Task 3: Construct a feature map

In this task, you will record a sequence of images that include a stationary, flat picture in the lab. You will then work on developing a map of a set of tracked features and identify the plane of the flat object in the feature map. This task will most likely need to be completed outside of the lab time slot, and will make up a significant portion of your lab report. For more hints on completing this section, see the comments in **l3_mapping.py**. You do not need to use the variables as we've set them up in l3_mapping.py, they are just suggested guidelines.

1) ~~While the robot is running start the ROS node **l3_data_saver.py**. It will save the images stream and robot pose matrices in a new folder, named l3_mapping_data, in the current working directory. The pictures will be labeled 0-N and have corresponding poses in tf.mat. Open the pose file to confirm that there are an equal number of poses and images.~~
    a. ~~Type s and hit enter to save the data and close the node.~~

2) ~~Place the flat object in the environment near the Turtlebot, and record a sequence where the~~

~~robot drives backwards, forwards, and rotates significantly, but always keeps the target object in view. Try to minimize the number of non-stationary objects in the camera's view.~~
1 and 2 removed since half of the students cannot complete them.

3) You will now reuse some of the tools from part 2 to detect and match features, but it will operate on stored images instead. You will first detect features on the **first image,** store their descriptors, and then match detected features on all future images to these features. You will then need to store the features in a way that ensures that you keep track of the (u, v) image coordinates of each feature, if it is detected, for each image. Specifically, when you're done this step, you should have an array of shape (num_images, num_features, 2). Modify the feature detection, tracking and matching pipeline from part 2 to operate on stored images. Some notes on cv2 functions that you will use:
    a. `matches = self.bf.match(query_descriptors, train_descriptors)` returns a list of match objects that have the attributes trainIdx and queryIdx. These are ids are associated with the train descriptors and query descriptors respectively.
    b. `kp_new, des_new = self.orb.compute(gray, kp)` returns your keypoints and descriptors. Kp_new in this case will contain an attribute pt which is the tuple (x_pixel, y_pixel).

4) In addition to the images, you will now have the recorded poses of the robot camera optical frame. Use these poses to estimate the position of each tracked feature in a common coordinate frame. The starter code is already set up for you to use the initial pose of the camera as the common frame.
    a. There are several ways to approach this problem. Probably the simplest (and recommended) way is based on triangulation and a least-squares formulation. For more details on this approach, see Section 7.1 of Szeliski's Computer Vision textbook (available for free at szeliski.org/Book).
    b. We have included code for visualizing your feature point cloud, a plane fitted to the point cloud, and an image showing the same feature locations against the first image in the trajectory to help you visualize if your mapping function is working. In your report, you may include these images, but you should also include others (such as different views of the point cloud).
    c. We recommend that you use some feature rejection techniques, such as rejecting features with the largest matched descriptor distance from one another or rejecting features that aren't seen in enough images. We leave these design decisions up to you, though you should comment on them and their effects in your report.
    d. Regardless of how good your mapping technique is, you will almost certainly have some outlier points that do not lie close to the plane that all of the others lie in, though this should be no more than 5-10% of your features (and ideally even less).

5 Lab Report

This lab is a challenging exercise in using ROS, OpenCV and the Turtlebot, and may require significant independent investigation to create a working solution. The report for this lab is the only deliverable for the lab portion of the course, and needs only cover those aspects of your work that demonstrate understanding and the proper functioning of your code on real data. The report should be as concise as possible and include the following discussion and results:

1) ~~Report your calibration parameters and images showing the rectified images of the calibration target.~~ Removed since half of the students cannot complete this.

2) Describe your feature detection, description and matching method, any parameters you selected or modifications you made to the provided instructions, and present 3 pairs of images and their matches. Discuss what you uncovered in terms of match quality for the 3 image pairs, and select the pairs in a way that demonstrates both strengths and weaknesses of feature-based front ends.

3) Present a derivation for your feature map construction. We want to see a mathematical formulation of your triangulation technique, as well as an algorithmic description of your pipeline for organization and possible rejection of features.

4) Include your code for part 3 in an appendix and submit a single PDF report.

6 Concluding Remarks

This lab exposes you to the implementation challenges of getting visual localization and mapping methods to work in the real world. In fact, the lab environment is still rather benign compared to the visual challenges that field robotics applications require. Mining, forestry, autonomous vehicles, oceanic vessels all require robust localization capabilities in far more severe conditions, and robotic vision remains a challenging open field to this day. We hope this lab gave you a little taste for how much fun these challenges can be.

7 Additional Resources

1. Introduction to ROS, ROB521 Handout, 2019.
2. Robotis e-Manual, `http://emanual.robotis.com/docs/en/platform/turtlebot3/overview/`.
3. "SSH: Remote control your Raspberry Pi," The MagPi Magazine, `https://www.raspberrypi.org/magpi/ssh-remote-control-raspberry-pi/`.
4. Official ROS Website, `https://www.ros.org/`.
5. ROS Wiki, `http://wiki.ros.org/ROS/Introduction`.
6. Useful tutorials to run through from ROS Wiki, `http://wiki.ros.org/ROS/Tutorials`.
7. ROS Robot Programming Textbook, by the TurtleBot3 developers, `http://www.pishrobot.com/wp-content/uploads/2018/02/ROS-robot-programming-book-by-turtlebo3-developers-EN.pdf`.