Outdoor Performance Analysis of monocular ORB_SLAM2 on Varied Lighting and Weather Conditions

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Abstract

We are here to present an investigation of the influences of lighting and weather conditions on the outdoor performance of monocular ORB_SLAM2[1] algorithm. Specifically, we performed monocular ORB_SLAM2 on Oxford Robotcar Dataset[2], with different conditions (overcast, rain and night) to estimate the trajectories. We calculated the trajectory errors and also did an inspection on the continuity of estimated trajectories. After the analysis, the major findings are: the precision of estimated trajectory depends largely on the lighting conditions. In particular, the precision of the estimated trajectory is the best in overcast weather and the worst at night. The tracking performance is significantly influenced by the image exposure. Overexposure and underexposure in the large scale would deteriorate the tracking ability and cause ORB_SLAM2 to relocalize and reinitiate, which results in a scale drift.

Introduction

During the last decade, more and more attention has been drawn on autonomous driving, in which a vehicle senses its environment and navigates without human input. To get an understanding of its surrounding, the unmanned vehicle has to solve the computational problem of simultaneous localization and mapping (SLAM) to construct or update a map of an unknown environment while simultaneously keeping track of its own location and pose. SLAM algorithms are usually specific to the available resources, such as monocular camera, stereo camera or lidar, and thus achieve different results as a tradeoff with operational compliance. Examples of famous SLAM algorithms include PTAM[3], MonoSLAM[4], ORB-SLAM[5], RGBD-SLAM[6] and LSD-SLAM[7].

ORB_SLAM2 is a state-of-the-art, real-time SLAM library to compute camera trajectory and a sparse 3D reconstruction from various environment. It contains a complete system of monocular, stereo and RGB-D cameras, including map reuse, loop closing and relocalization capabilities[1]. It quickly gained favor and became one of the most widely used SLAM algorithms. However, the outdoor performance of SLAM algorithms, especially those based on monocular cameras, depends largely on the lighting and weather conditions and there is right now no paper analyzing the outdoor performance of monocular ORB_SLAM2 with different environment conditions.

In this paper, we generally focus on exploring the influences of lighting and weather conditions on the outdoor performance of monocular ORB_SLAM2 algorithm. More specifically, we compared the trajectory error and tracking continuity of monocular ORB_SLAM2 algorithm in overcast, rain and night conditions.

In general our findings are:

1. The trajectory error depends largely on the lighting conditions. In particular, the precision of the estimated trajectory is the best in overcast weather and the worst

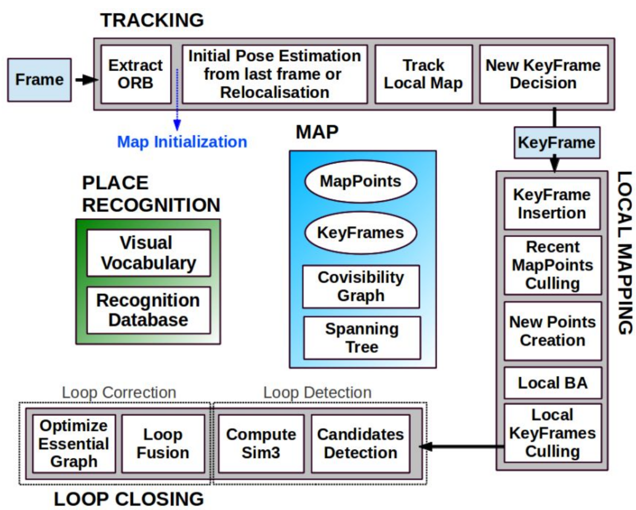
at night.

2. The tracking performance is significantly influenced by the image exposure. Overexposure and underexposure in the large scale would deteriorate the tracking ability and cause ORB_SLAM2 to relocalize and reinitiate, which results in a scale drift.

Algorithm

The main characteristic of monocular ORB_SLAM2 is that it utilizes the same ORB features for the entire SLAM process, including tracking, mapping and place recognition. The features are fast and easy to be extracted and also robust to rotation and scale. They also present a good invariance to camera auto-gain and auto-exposure, and illumination changes[1].

Monocular ORB_SLAM2 performs bundle adjustment to optimize a local window of keyframes and points, trying to remove outliers and achieve a better estimation. Essential Graph Optimization is performed during loop closing to correct the potential scale drifting for monocular SLAM[4].



System threads and modules of ORB_SLAM2[1]

Dataset

We used Oxford Robotcar Dataset for this project. It contains over 100 repetitions of a consistent route through Oxford, UK, captured over a period of over a year. The dataset captures many different combinations of weather, traffic and pedestrians, along with longer term changes such as construction and roadworks[2].

The images we used:

1. Dataset 2015/08/13 16:02:58 GMT, Bumblebee XB3 stereo left images, overcast.
2. Dataset 2015/02/03 19:43:11 GMT, Bumblebee XB3 stereo left images, night.
3. Dataset 2015/10/29 12:18:17 GMT, Bumblebee XB3 stereo left images, rain.

Note that we only used part of the dataset instead of the entire route, just for simplicity.

Setup

Here are some details about the setup and implementation of monocular ORB_SLAM2.

1. Camera calibration and distortion parameters (OpenCV format) :
    a. Camera.fx: 964.828979
    b. Camera.fy: 964.828979
    c. Camera.cx: 643.788025
    d. Camera.cy: 484.407990
    e. Camera.k1: 0.0
    f. Camera.k2: 0.0
    g. Camera.p1: 0.0
    h. Camera.p2: 0.0
    i. Camera.k3: 0.0

    (Note: To preprocess the images, we used the python development kit provided for batch image demosaicing and undistortion.)
2. ORB Extractor (Number of features per image): 4000
3. ORB Extractor Fast threshold
    a. iniThFAST: 10
    b. minThFAST: 7

    (Note: Firstly we impose iniThFAST. If no corners are detected we impose a lower value minThFAST)
4. Since examining scale drifting is beyond the scope of our project, and given that the selected road sections in the dataset don't have a loop for loop closure correction, we assume that the scale is constant for the entire course. Note that this would give a much bigger absolute trajectory error, but we can still find the overall relation between the results of different weathers and lighting conditions.

Result & Analysis

	Mean Absolute Trajectory Error (m)	Max ATE (m)	Min ATE (m)
Overcast	6.6224	18.2421	0.3050
Rain	13.7752	21.6730	0.6450
Night	16.3982	24.9120	0.4300

Absolute trajectory error with constant scale (Assuming no scale drifting)

From the above diagram we can conclude that weather and lighting conditions do affect the precision of monocular ORB_SLAM2. In particular, the mean absolute trajectory error and max absolute trajectory error are the largest for the night condition and the smallest for the overcast condition. The results of rain and night conditions are more close to each other, possibly because the lighting is insufficient in both cases. The min ATE for the rain condition is the largest, possibly because of the interference of rain drop on camera images which distorted the visual features.

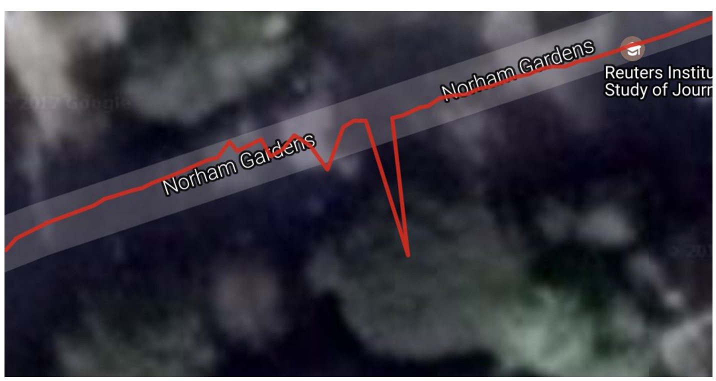
	Inspection of estimated trajectory for the continuity of SLAM localization
Overcast	ORB_SLAM2 lost track and re-initiated when facing a strong backlit of afternoon sun, with large-scale overexposure.
Rain	ORB_SLAM2 lost track but was able to relocalize itself after a strong left turn.
Night	ORB_SLAM2 lost track when facing a large-scale underexposure, and was reinitiated after relocalization failure.

Continuity inspection on the SLAM localization

From the above diagram we can see that ORB_SLAM2 is especially vulnerable to the loss of image information, caused by over and underexposure. The algorithm would also lose track in condition of large rotational motion, but it does a good job at relocalizing the camera pose.

Difficulties and Future Work

1. The Oxford Robotcar dataset is still under development. Unlike KITTI dataset which provides a complete benchmark functionality, Oxford Robotcar dataset doesn't provide the ground truth camera poses. We tried to use the GPS/IMU data to generate the ground truth trajectories, but the timestamps don't match with the image timestamps. Also the discontinuity on GPS data makes it hard for us to continue using GPS as ground truth. As a result, we used visual odometry relative pose estimates as a reference local pose source. This is only a reference and not a ground truth relative pose system.



Discontinuity of GPS Data in Oxford Robotcar Dataset

2. As all of the monocular SLAM systems do, ORB_SLAM2 would face the problem of scale drifting, which would have a significant influence on the absolute trajectory error calculation. In this project we assume that the scale is constant for the entire route, which makes the calculation much easier but definitely not the case in reality. For future investigations, we can use dataset with loops so that ORB_SLAM2 can perform Bundle Adjustment with monocular observations which allows for accurate trajectory estimation with metric scale. Moreover, we can investigate on the influences of weather and lighting

conditions on stereo data, which can avoid the scale drifting problem.

3. With smaller number of features per image (such as 1000 or 2000), the algorithm cannot even initialize in rain and night conditions. As a result, we chose 4000 number of features per image to get a better initialization. However, this number is not a result of careful investigation. In future work, we can also play around more with the parameters of ORB_SLAM2 to achieve a better result in general.

Conclusion

We have presented the performance testing of ORB_SLAM2 with monocular datasets in different environments and weather conditions. Although there are difficulties in the functionality of datasets and in the scale calculation, we are still able to compare the performances clearly. According to the result, ORB_SLAM2 performs best in overcast weather condition, where the lighting is stable. The absolute trajectory error is the highest in the night condition, where the camera is constantly underexposed and number of features captured are low. In future work, we might improve the evaluation method by determining a best scale for the SLAM result, and tweaking on the parameters of ORB_SLAM2 to maximize its result in each condition.

References

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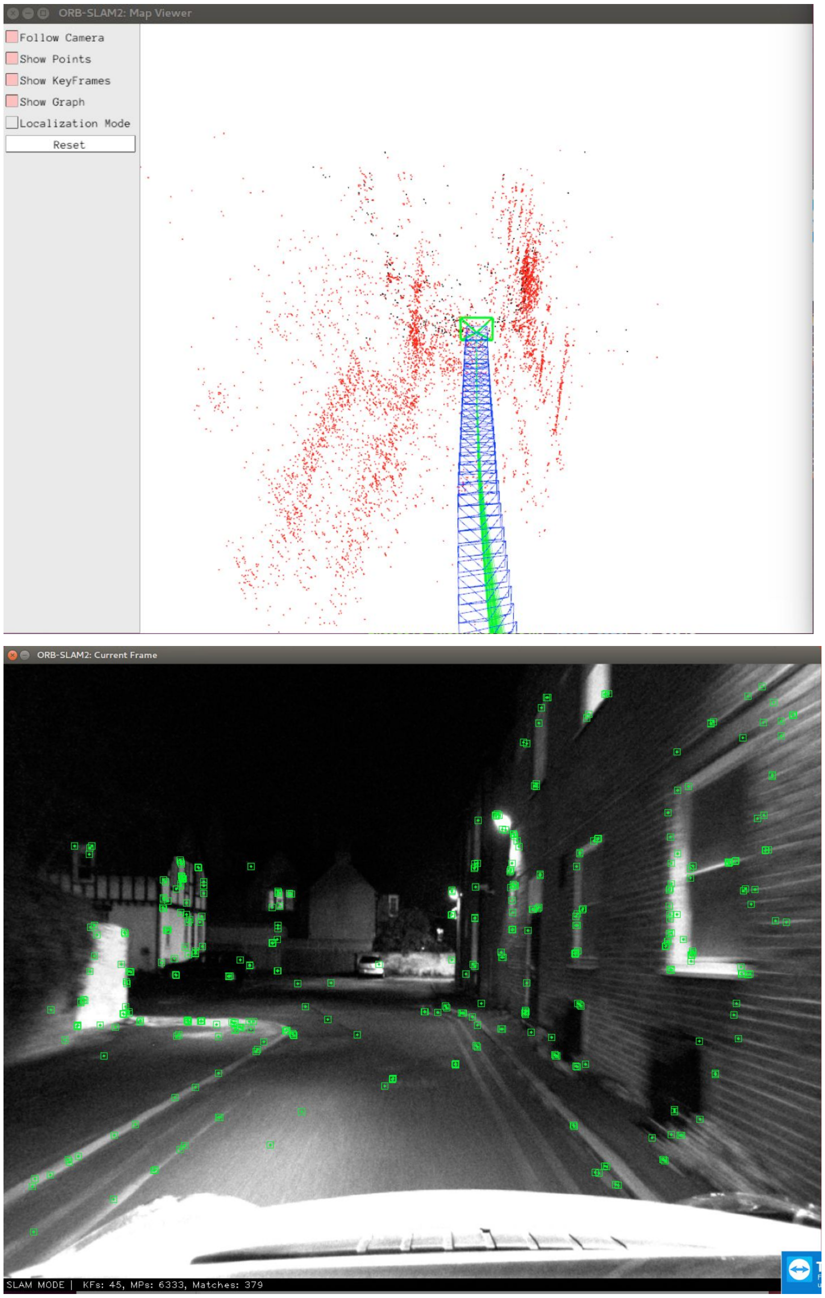

Monocular ORB_SLAM2 with consistent tracking

Monocular ORB_SLAM2 after losing track