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**Place Recognition and Localization for
Multi-Robot SLAM**

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Abstract

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Keywords: Dissertation, keywords.

Acknowledgement

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Acronyms

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Symbols

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Chapter 1

Introduction

1.1 Background

SLAM(Simultaneous localization and mapping) is a key component in mobile autonomous systems. It describes the ability of a vehicle, once placed in an unknown environment, to explore and map that environment, while at the same time estimating its own position in the environment, using only its onboard sensing capabilities.

SLAM systems can be accomplished by both single or multiple robots. Multiple-robot SLAM or MRSLAM, offer several advantages compared to there single robot counterpart, for example:

- Robustness to single robot failure,
- Quicker exploration of environments in time critical SaR(Search and Rescue) mission.

However, Adapting SLAM technology to multiple-robot scenario brings some new changes as identified by Saeedi et al [2]:

- Relative Poses of Robots. In multiple-robot SLAM, the map provided by each robot in its own reference coordinates is called the local map. It is difficult task to integrate all of the local maps provided by the other robots to generate a global map of the environment, because the required alignments or transformation matrices, which relate these maps to each other, are in general unknown.

- Closing Loops. Loop closure, is defined as identifying a place observed previously but not very recent. Solving this problem for a team of multiple robots requires using all resources of information from individual robots.in Multi-robot SLAM, various events can trigger loop closure, such as direct encounter of the robots or rendezvous and indirect encounter, when the robots see the same area of features in the world.
- Communications. Availability of a medium for data sharing among robots is an important requirement in multiple-robot SLAM. Information between robots can be exchanged via communication channels. The quality of the communication channels is dependent on the environment. For instance, communication issues are a challenging problem for a team of robots in underwater environments, where the environment imposes limitations on the bandwidth and data rate.

Because of the limitation of the difficulties mentioned above, the development of multiple-robot SLAM is much slower than single-robot SLAM. Finding a solution to these problem will push the adaption of SLAM technology to a new level.

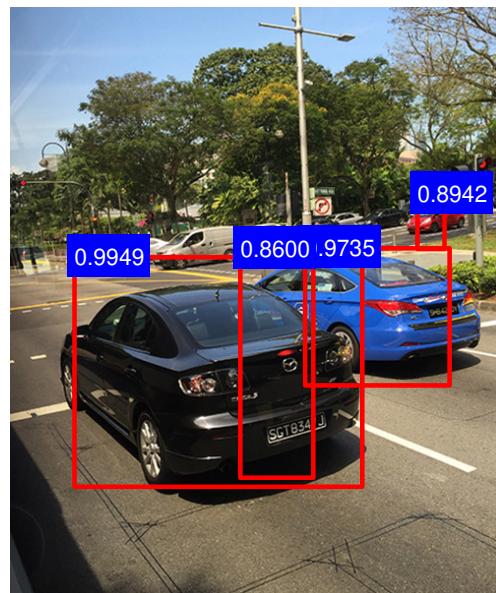


Figure 1.1: TBD

1.2 Motivation and Objectives

Recently, some solutions for Multi-robot SLAM systems have been proposed. [3]

1.3 Major contribution of the Dissertation

1. Evaluation of CORB-SLAM on NTU datasets collected by a cluster of multi ground robots or multi hybrid robots.
2. Modification of CORB-SLAM to improve its stability and accuracy.
3. Combination of CORB-SLAM and shade dealing algorithms to enhance its ability to deal with illumination changes.

1.4 Organisation of the Dissertation

This dissertation is organised into several chapters:

1. Chapter 2 briefly outlines the development of visual SLAM technique. Firstly, the classic structure of visual SLAM system is introduced, and the critical algorithms involved are elaborated. The existing solutions are classified into single-robot and multi-robot systems. This chapter also explores prior work in shade dealing algorithms required to implement life-long SLAM.
2. Chapter 3 explains the methodology used in this dissertation to improve the stability and accuracy of CORB-SLAM, and how to combine illumination variance method with CORB-SLAM system to enhance the ability of CORB-SLAM to deal with illumination changes.
3. Chapter 4 shows the results of (i) the evaluation of CORB-SLAM with NTU datasets. (ii) the evaluation of illumination variant CORB-SLAM with datasets collected under different illumination conditions.
4. Chapter 5 analysis the results demonstrated in chapter 4 in detail, discussing the improvement and the disadvantages.

5. Chapter 6 summarizes the work done in this dissertation, and comments on the significance and some potential applications of the proposed solutions.

Chapter 2

Literature Review

2.1 Visual SLAM

2.1.1 Introduction

Simultaneous Localizaiton and Mapping (SLAM) is a technique to obtain 3D structure of an unknown environment and sensor motion in the environment. After years of development, SLAM-based application have become widely broadened such as computer vision based 3D modeling, augmented reality(AR)-based visualization and self-driving cars.

In early SLAM algorithms, there exit many different modalities of sensors integrated in SLAM systems, such as rotary encoders, light detection and ranging radar (LiDAR), inertial sensors, GPS and cameras. In recent years, SLAM using cameras only, specifically referred to as visual SLAM (vSLAM), has been actively discussed because the sensor configuration is simple, low-cost, and contains abundant information. But meanwhile this technique also brings more difficulties than others using integrated sensors [4].

vSLAM algorithms have proposed widely in the field of computer vision, robotics and AR. The low requirement on the modalities of sensors, requiring cameras only, is the major advantage of vSLAM technique, so that it is very suitable for low-cost unmanned vehicles, robots with limited load capacity and power supply like drones, or mobile devices such as camera-mounted tablets or smart phones.

However, the difficulties brought by vSLAM can not be ignored. Instead of obtaining depth and location information directly from LiDAR, GPS or depth camera in integrated SLAM systems, vSLAM technique needs to compute all these information from color or gray images, which reduces stability and accuracy for several estimation steps involved in this process. Also obviously the computational cost are significantly higher. Therefore, the problem of how to improve the performance and reduce computational cost of vSLAM has always been widely concerned.

2.1.2 Framework

The framework of visual SLAM is mainly composed of five modules as follows:

1. Sensor Data Collection
2. Visual Odometry
3. Global Map Optimization
4. Loop Detection
5. Mapping

This framework is illustrated in Figure 2.1.

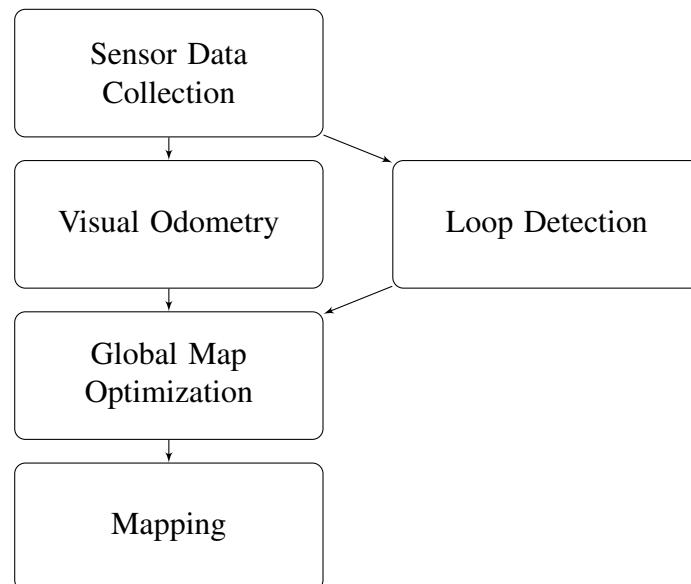


Figure 2.1: Classic structure of Visual SLAM

Sensor data collection module in visual SLAM systems, is responsible to read and preprocess the image information collected from cameras.

In the module of visual odometry (VO), the reconstructed map is tracked in the image to estimate the camera pose of the image with respect to the map. In order to do this, feature tracking or feature matching is executed to obtain 2D-3D correspondences between the image and the map. Then, the camera pose is computed by solving the Perspective-n-point (PnP) problem from the correspondences [5, 6].

The other module is loop detection, or loop closing, which is a technique to acquire the reference information. In this module, loop closure is detected by matching a current image with previously acquired images. If a closed loop is detected, it means one of the previously observed place is revisited. In this case, the accumulative error can be estimated. The closed loops and the estimated accumulative error will be sent to the next module of global map optimization.

The next module is global map optimization. The reconstructed map includes accumulative estimation error according to the movement distance of the camera. To suppress the accumulative error, the global map optimization is usually performed. In this module, the map is refined according to the consistency of the entire map. When a place is revisited and a closed loop is detected, reference information that represents the accumulative error can be computed. Then global map optimizer can suppress the accumulative error using loop closure from the reference information as a constraint.

Mapping is the last module. In this module, the map is constructed and expanded by computing the 3D structure of the environment according to the information collected and computed in the prior modules.

2.1.3 Related Techniques

ORB Features

[7]

Bag-of-Words Fast Place Recognition

[8]

Bundle Adjustment

[9] [10]

2.1.4 Algorithms

According to the different types of the information used in VO, the existing vSLAM algorithms can be categorized into feature-based, direct, and RGB-D camera-based approaches: (i) Feature-based approaches attract and track feature points, (ii) Direct approaches track a whole image without detecting feature points, (iii) RGB-D approaches use both monocular RGB images and its depth. Some popular vSLAM algorithms proposed in recent years are listed as follows:

Feature-based Approach

1. MonoSLAM

MonoSLAM is the first monocular vSLAM, developed in 2003, by Davison et al. [11,12], which is considered as the representative method in filter-based vSLAM algorithms. In MonoSLAM, An extended Kalman filter (EKF) is used to simultaneously estimate the camera motion and 3D structure of an unknown environment. 3D positions of feature points and 6 degree of freedom (DoF) camera motion are represented as a state vector in EKF. The EKF in MonoSLAM assume uniform motion as a prediction model, and a result of feature point tracking as the observation. New feature points are added to the state vector depending on camera movement. The initial map is created by observing a known object where a global coordinate system is defined. In conclusion, there are two components in MonoSLAM system:

- (a) Map initialization, done by using a known object.
- (b) 3D positions of feature points and camera motion, estimated using EKF.

the limitation of this algorithm is its computational cost increases proportionally with the size of an environment. In large environments, the number of feature points increase causing the size of the state vector to be large. Therefore, real-time performance is difficult to achieve in large environments.

2. PTAM

In order to solve the problem of computational cost in MonoSLAM, Parallel Tracking and Mapping (PTAM) proposed in [13] split the tracking and the mapping tasks into different threads. These two thread are running in parallel, then the computational cost in the mapping thread have no effect on tracking. As a result, bundle adjustment (BA) which requires extra computational cost in optimization can be added in the mapping. This means the tracking thread can estimate camera motion in real-time, and meanwhile the mapping thread can estimate accurate 3D positions of the features points with higher computational cost, with causing no effect on the real-time performance of the tracking thread.

A significant of PTAM is to firstly introduce the concept of keyframe. PTAM is the first vSLAM algorithm to use keyframe-based mapping. In the mapping, 3D positions of new feature points are computed using triangulation at certain frames called keyframes. To achieve accurate triangulation, an input frame is selected as a new keyframe, when a large disparity is measured between the input frame and the previous keyframes. Also, a new relocalization algorithm [14] in tracking is employed in the newer version of PTAM, which uses a randomized tree-based feature classifier to match input frames with keyframes.

In summary, PTAM has the following four components:

- (a) Map initialization, done by the five-point algorithm [15].
- (b) Camera pose estimation, from matched feature points between the input image and map points.
- (c) 3D positions of feature points estimation, by triangulation computation, and optimized by BA.
- (d) Tracking process, recovered by a randomized tree-based searching.

3. ORB-SLAM

There have been proposed many SLAM algorithms based on PTAM. ORB-SLAM, one of the most popular vSLAM algorithm proposed in [16, 17], also based on PTAM. The most important improvement of ORB-SLAM compared to PTAM, is

ORB-SLAM employs a new loop detection thread. The details of ORB-SLAM are reviewed in Chapter 2.1.5.

Direct Approach

1. DTAM

Dense Tracking and Mapping (DTAM) was proposed by Newcombe et al. in [18], is fully direct method. In DTAM, the input image is compared with synthetic view images generated from the reconstructed map. This is equivalent to registration of an image on the 3D model of a map, which can be efficiently implemented on GPU. The initial depth map is created using stereo measurement like PTAM. In summary, there are three main components in DTAM:

- (a) Map initialization, done by stereo measurement.
- (b) Camera motion estimation, by synthetic view generation from the reconstructed map.
- (c) Pixel depth information estimation, using multi-baseline stereo, then optimized by considering space continuity.

DTAM is optimized to achieving real-time processing on mobile phones in [19].

2. LSD-SLAM

Large-scale direct monocular SLAM (LSD-SLAM), proposed in [20], is another leading direct method, which follows the idea from semi-dense VO [21]. Compared to DTAM which reconstructs full areas, the reconstruction targets are limited to areas only which have intensity gradient in LSD-SLAM. Therefore, in LSD-SLAM, textureless areas are ignored where it is difficult to estimate depth information. In the mapping, initial depth values for each pixel is set to random values, and then optimized considering photometric consistency. In conclusion, four components of LSD-SLAM are as follows:

- (a) Initial depth value, set as random values.

- (b) Camera motion, estimated by synthetic view generated from the reconstructed map.
- (c) Area reconstructed, limited to high-intensity gradient areas.
- (d) 7 DoF pose-graph optimization, employed to obtain geometrically consistent map.

In [22], they optimized the LSD-SLAM algorithms to be able to run on mobile phones with real-time performance, and also evaluate the accuracy for low-resolution images. In [23, 24], LSD-SLAM is extended to stereo camera and omni-directional cameras.

RGB-D Approach

Recently, with structure light-based RGB-D cameras such as Microsoft-Kinect getting cheaper and smaller, RGB-D SLAM algorithms with RGB-D camera become more popular and affordable.

1. KinectFusion

KinectFusion was proposed by Newcombe et al. in [25]. In KinectFusion, a voxel space is used for representing the 3D structure of the environment. The 3D structure of the environment is reconstructed by combining obtained depth maps in the voxel space, and camera motion is estimated by the ICP algorithm using an estimated 3D structure and the input depth map, which is depth-based vSLAM and it is optimized with GPU to achieve real-time performance.

In [26], KinectFusion is optimized to run on mobile devices in real time. To

2. SLAM++

SLAM++ was proposed as an object level RGB-D vSLAM algorithm by Salas-Moreno et al in [27]. In SLAM++, several 3D objects are registered into the database in advance, and these objects are recognized in an online process. The estimated map is refined by recognizing 3D objects, and 3D points are replaced by 3D objects to reduce the amount of data.

As a similar algorithm, another real-time segmentation method for RGB-D SLAM in [28] by Tateno et al. Segmented objects are labeled and then used as recognition targets.

2.1.5 ORB-SLAM

One of the state-of-the-art vSLAM solutions for single-robot systems is ORB-SLAM, initially proposed in [16], and upgraded to a second version in [17].

ORB-SLAM is a feature-based monocular SLAM system that operates in real time, in small and large, indoor and outdoor environments. In the proposed work in [16], ORB-SLAM is built on the main ideas of PTAM, the place recognition work of Gálvez-López and Tardós [8], the scale-aware loop closing of Strasdat et. al [29] and the use of covisibility information for large scale operation [30], [31]. As a novel monocular SLAM system, the main contributions of ORB-SLAM are:

1. !!!The same features are used in all tasks: tracking, mapping, relocalization and loop closing. Using same features makes the system more efficient, reliable and simple. And using ORB features allows real-time performance without GPUs, with good invariance to changes in viewpoint and illumination.
2. Real time performance in large environments. The tracking and mapping modules focus in a local covisible area, independent of the global map, thanks to the use of a covisibility graph.
3. Real time loop closing. The optimization of a pose graph called the Essential Graph is adapted to realize real time loop closing performance. The Essential Graph is built from loop closures links, strong edges from the covisibility graph and a spanning tree maintained by the system.
4. Real time camera relocalization with significant invariance to viewpoint and illumination. This allows recovery from tracking failure and also enhances map reuse.
5. A new automatic and robust initialization procedure based on model selection that permits to create an initial map of planar and non-planar scenes.

- A survival of the fittest approach to map point and keyframe selection that is generous in the spawning but very restrictive in the culling. This policy improves tracking robustness, and enhances life-long operation because redundant keyframes are discarded.

ORB-SLAM system, see on Figure 2.2, incorporates three threads that run in parallel: tracking, local mapping and loop closing.

The tracking thread is in charge of localizing the camera with every frame and deciding when to insert a new keyframe. The module firstly match current frames with previous frames, and optimize the pose using motion-only bundle adjustment. If the

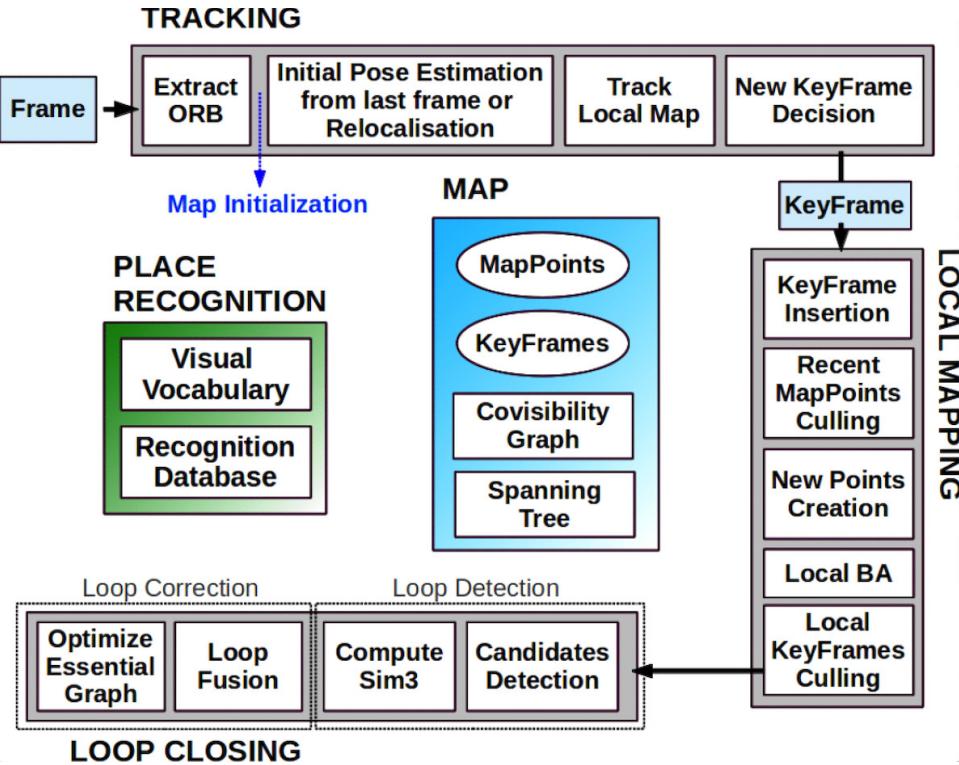


Figure 2.2: ORB-SLAM system overview.

2.2 Multi-Robot Algorithms

2.2.1 Multi Ground Robot System

2.2.2 Multi Hybrid Robot System

2.2.3 CORB-SLAM

Proposed by F.Li et al. in [1], CORB-SLAM is a vSLAM algorithm focusing on multi-robot systems. As presented in Figure 2.3, the system of CORB-SLAM consists of robot-end clients and a server.

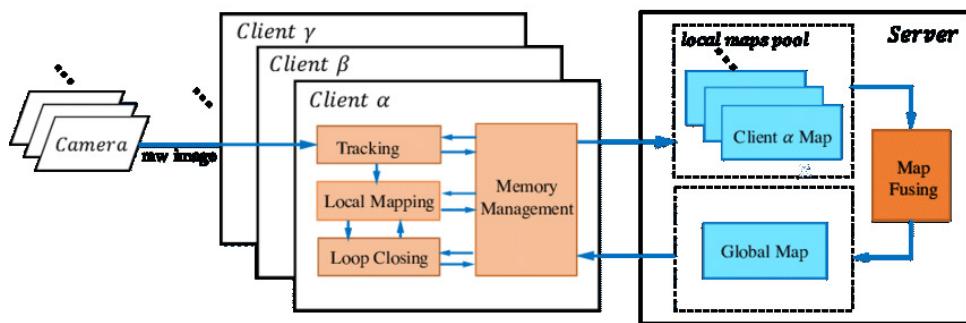


Figure 2.3: The framework of CORB-SLAM system.

Robot-end SLAM Client

The robot-end client of CORB-SLAM is an ORB-SLAM client extended to have the functionality to communicate with the server, transmitting the keyframe information, with all functions and modules in original ORB-SLAM as listed in Chapter 2.1.5 reserved.

Map Fusing in the Server

In the server, the map fusing module receives and fuses the local maps from the clients, achieving an optimized global map. The map fusing algorithm is shown in Figure 2.4, including two main parts: map overlap detection and local-map fusion.

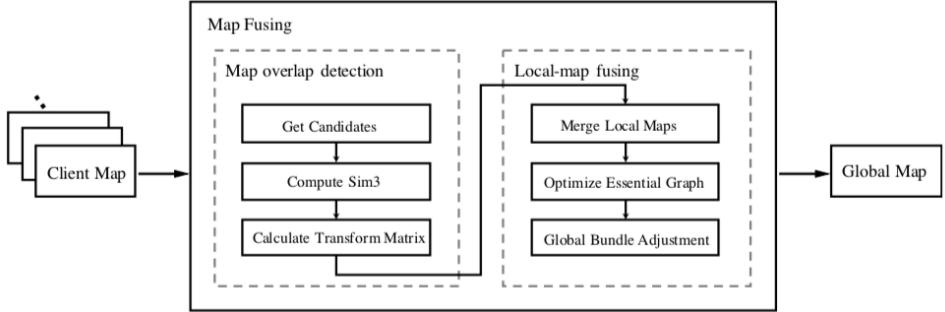


Figure 2.4: The flowchart of Map Fusing module.

1. Initializing global map

Initially,

2. Map overlap detection

To

3. Local map fusing

To

2.3 Illumination Variance

2.3.1 Appearance Change From Illumination

For vision systems concerned with localizing in known environments, dealing with appearance changes is an ongoing challenge. Appearance changes can result from several sources, such as (i) different lighting conditions, (ii) varying weather conditions, and (iii) dynamic objects like pedestrians or vehicles.

In previous work of Colin McManus et al. , they demonstrated how to leverage knowledge of prior 3D structure to suppress distracting objects for improved pose estimation in busy urban environments [32], and how to cope with long-term appearance variation caused by changing weather conditions [33]. In [34], they proposed a new approach to address problem (i) named as Illumination Variance Approach.

Appearance change caused by different lighting conditions in (i) is illustrated in Figure 2.5 with pictures selected from St Lucia dataset [35]. Compared to approaches



(a) pic1.



(b) pic2.

Figure 2.5: Appearance changes caused by different lighting conditions. Pictures are selected from St Lucia dataset corresponding to the car rides recorded on 10/09/2009 at 8:45 am and at 2:10 pm

proposed in [32] and [33], illumination variance approach is not model-based, requiring less computational cost. And in most of applications of vSLAM, appearance changes caused by (i) are a more common problem than (ii)(iii). Therefore, how to combine illumination variance approach with multi-robot SLAM algorithms, to improve the performance of place recognition in changing illumination conditions, is the major objective focused on in this work.

2.3.2 Illumination Variance

Illumination variance approach proposed in [34], is a simple method based on only one equation computing illumination variant images. The basic idea of this approach is to map color images to an illumination invariant color space, where illumination change caused by different lighting condition like shade can be suppressed. The mapping equation is presented in Equation 2.1.

$$I = \log(G) - \alpha \log(B) - (1 - \alpha) \log(R) \quad (2.1)$$

where, R, G, B are the color channels of the input image, and I is the resultant illumination invariant image. As shown in 2.2, α is a parameter which depends on the peak spectral responses of each color channel ($\lambda_R, \lambda_G, \lambda_B$), which are usually available in camera specifications.



(a) pic1.

(b) pic2.

Figure 2.6: An example of illumination invariance application in St Lucia dataset. It shows how this approach suppress the effects caused by sun

$$\frac{1}{\lambda_G} = \frac{\alpha}{\lambda_B} + \frac{1-\alpha}{\lambda_R} \quad (2.2)$$

Therefore, considering the peak spectral responses, α can be easily calculated as exposed in Equation 2.3.

$$\alpha = \frac{\left(\frac{\lambda_B}{\lambda_G} - \frac{\lambda_B}{\lambda_R}\right)}{\left(1 - \frac{\lambda_B}{\lambda_R}\right)} \quad (2.3)$$

The influence of applying the illumination invariant transformation is showed in Figure 2.6.

2.3.3 ??? Life-Long SLAM

An open source toolbox named as OpenABLE, for life-long visual localization is implemented in [36]. The proposed implementation in [36] employs the philosophy of the topological place recognition approach named ABLE introduced in [37–39] which uses illumination variant images for relocalization.

A graphic representation about how the methodology proposed by OpenABLE is showed in Figure 2.7.

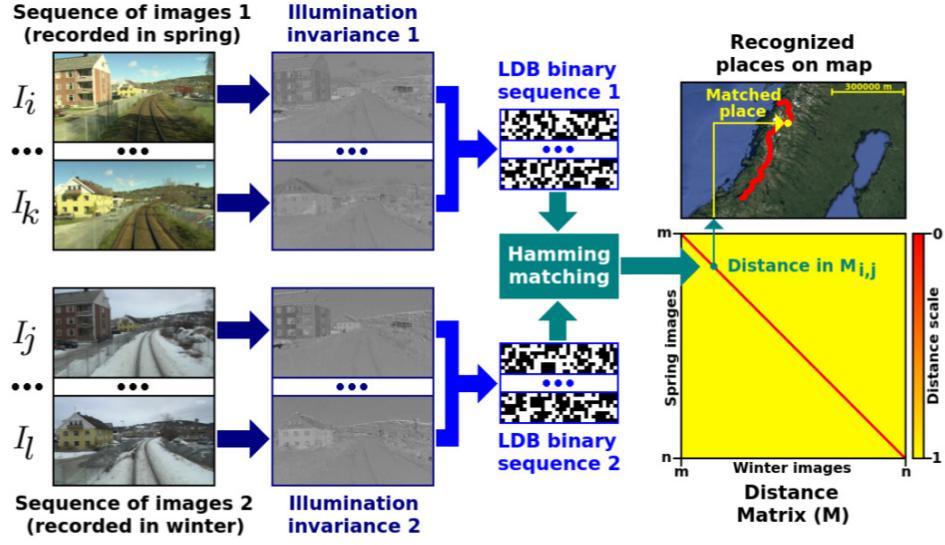


Figure 2.7: A graphic representation about how the methodology proposed by ABLE works.

The limitation of illumination variance approach is the transformation process produces resultant images with low resolution because all pixel values are turned into log values. These low-resolution resultant images still can be used as the input images of visual topological localization where high resolution images are actually not needed. But in the mapping task, illumination variant images are too blurry to estimate camera motion and then reconstruct the map. Therefore, to improve the mapping performance in changing illumination conditions, rgb images and illumination variant images are both needed to perform relocalization and mapping, as the block-flow proposed in [3] presented in 2.8.

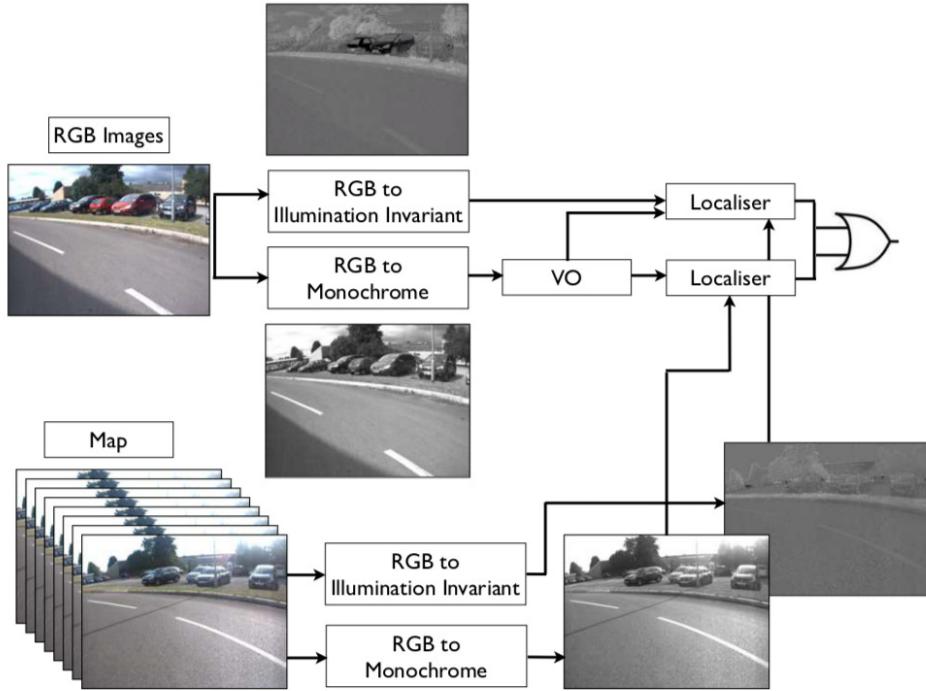


Figure 2.8: Block-flow diagram of the combined stereo localisation approach.

In the framework presented in 2.6, there is a second localizer making use of illumination invariant images in parallel with the main localization system. In [34], although the metric relative poses calculated from illumination variant images tends to be more noisy, the integrated localizer are less likely to fail if the scene appearance change is due to sunlight intensity direction or spectrum variation.

Chapter 3

Approach

3.1 CORBSLAM with Illumination Variance

To enhance the ability of CORB-SLAM to map in different illumination conditions and seasons, Illumination Variance method is combined into the map fusion modules of CORB-SLAM server. The block diagram of the integrated system is illustrated in Figure 3.1.



There is a figure

Figure 3.1: The block diagram of the modified system of CORB-SLAM integrated with illumination variance.

In the client end, the following modifications are made:

1. A new thread running in parallel is added to process the input frame to trans-

form into illumination variance images, and extract ORB keypoints in produced images (named as *II keypoints* in this paper).

2. II keypoint data is added into each frame as new member variables. And then following the CORB-SLAM methodology, only the integrated keyframes are transmitted to the server, which are serialized and packed by boost serialization library, and transmitted through ROS service.

Besides the above changes, the following modification are made in the server end:

1. A new keydataset containing II keypoint information.
2. A new illumination variance localizer running in parallel with the rgb localizer. When processing the input keyframe, a new localizer thread is started if the rgb localizer returns no result. The results from rgb and illumination variance localizer are currently added together in this work.

3.2 Quantitative Trajectory Evaluation Method

To evaluate the mapping performance, the proposed method in [40] is modified to multi robot case, and employed in this work.

The previous work of CORB-SLAM in [1] only provides a rough overview of the mapping result of the multi robot system, as seen in Figure 3.2.

In [34] and [36], the results of the illumination variance localization are also only briefly introduced, with no quantitative results given.

In this paper, mapping results of CORB-SLAM and CORB-SLAM integrated with is evaluated following the quantitative trajectory evaluation method proposed in [40]. Quantitative evaluation results of each datasets are demonstrated in several figures and tables including contents as follows, and see Section 4.2.1 as an example:

1. Ground truth trajectories of each partial sequence and the complete dataset for reference, e.g. Figure 4.9.
2. Mapping results of each client and fused map in server end, compared with ground truth trajectories, e.g. Figure 4.12.

3. Four charts of quantitative results, e.g. Figure 4.13, including
 - 1). Chart of relative translation error in meter, e.g. Figure 4.13(a).
 - 2). Chart of relative translation error in percent, e.g. Figure 4.13(b).
 - 3). Chart of relative yaw error in degree, e.g. Figure 4.13(c).
 - 4). Chart of scale error in percent, e.g. Figure 4.13(d).
 4. A table presenting numeric results of charts in 3, e.g. Table 4.4.
 5. (if applicable) The mapping results of CORB-SLAM mapping the entire sequence without partial sequences for reference, e.g. Figure 4.11.
 6. (if applicable) Charts of quantitative results of mapping the entire sequence for reference, in the same format of 3, e.g. Figure 4.10.
 7. (if applicable) A table presenting numeric results of charts in 6, e.g. Table 4.3.

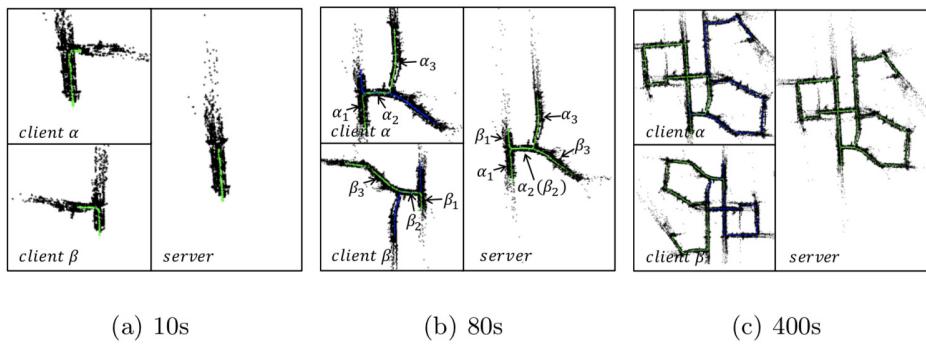


Figure 3.2: Mapping results of CORB-SLAM in [1].

Chapter 4

Test and Experiments

4.1 Datasets

Evaluation are performed in several datasets including KITTI stereo 2015 dataset [41], Oxford RobotCar dataset [42] and NTU dataset collected in NTU. The listing of used datasets is shown in Table 4.1

4.1.1 KITTI Visual Odometry Dataset

KITTI Visual Odometry 2012 is a part of KITTI Vision Benchmarck Suite, presented in [41,43]. KITTI datasets are captured by driving around a mid-size city, in rural areas and on highways. The recording platform is equipped with two high resolution stereo camera systems, capturing color and gray images, a Velodyne HDL-64E LIDAR, and an OXTS RT 3003 localization system which combines GPS, GLONASS, an IMU and RTK correction signals.

KITTI Visual Odometry Evaluation 2012 provides 11 sequences with ground truth trajectories for training, and another 11 sequences without ground truth for evaluation.

Table 4.1: Information of datasets used

| Datasets | Settings | Approx Scale | Diversity |
|----------|------------|--------------|--|
| KITTI | rural area | < 1 hour | one city, one weather condition, daytime |
| Oxford | city | 214 hours | one city, multiple weather conditions, daytime |
| NTU | campus | < 1 hour | one campus (NTU), one weather condition |

Example images are shown in Figure 4.1.



Figure 4.1: Example image in KITTI Visual Odometry 2012 dataset.

4.1.2 Oxford RobotCar Dataset

Oxford RobotCar Dataset is presented by Will Maddern et al. in [42], as a challenging dataset for autonomous driving. Collected over the period of May 2014 to December 2015, this datasets recorded images from 6 cameras mounted Nissan LEAF, along with LIDAR, GPS and INS ground truth. Images were recorded under different weather and illumination condition from 9:00 to 16:00 on average, from May to December. Example images is shown in Figure 4.2.



Figure 4.2: Example image in robotcar dataset.

The RobotCar platform is a Nissan LEAF equipped with sensors as following [42]:

1. Stereo Camera: Bumblebee XB3 trinocular stereo camera $\times 1$, 1/3" Sony ICX445 CCD, $1280 \times 960 \times 3$, 16Hz, 3.88mm lens, 66° HFoV, 12/24cm baseline, global shutter.
2. Monocular Camera: Grasshopper2 $\times 3$, 2/3" ICX285 CCD, 1024×1024 , 11.1Hz, 2.67mm fisheye lens, 180° , global shutter.
3. 2D LIDAR SICK LMS-151 2D LIDAR $\times 2$, 270° FoV, 50Hz, 50m range, 0.5° resolution.
4. 3D LIDAR: SICK LD-MRS 3D LIDAR $\times 1$, 85° HFoC, 3.2° VFoV, 4 panes, 12.5Hz, 50m range, 0.125° resolution.
5. GPS/INS Module: NovAtel SPAN-CPT ALIGN inertial and GPS navigation system $\times 1$, 6 axis, 50Hz, GPS/GLONASS, dual antenna.

The RobotCar platform and the sensor locations are demonstrated in Figure 4.3.

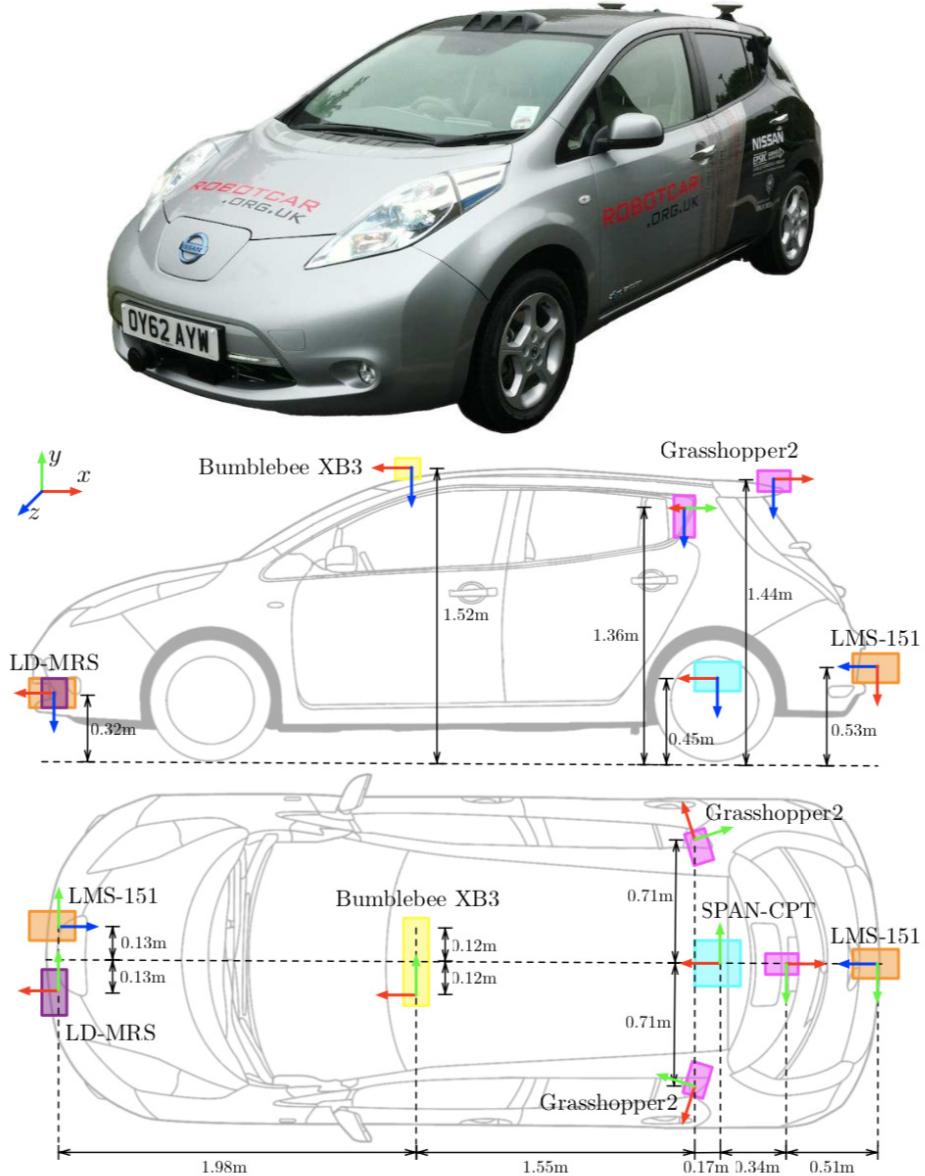


Figure 4.3: The robotcar platform and sensor location diagram.

RobotCar dataset is especially suitable to evaluate life-long SLAM systems, since it contains images taken in different hours of daytime under different illumination conditions, and in different seasons. The comparison between image in different illumination conditions and different seasons is shown in Figure 4.4.



(a) Image captured in 14:49 07/14/2014. (b) Image captured in 12:32 02/24/2015.

Figure 4.4: Comparison of images captured in the same location in different seasons in RobotCar dataset.

Table 4.2: Main characteristics of the rosbags in NTU Dataset used in the experiment.

| Bag No. | Data(M/D/Y) | Platform | Height(m) | Dep. Angle |
|---------|-------------|----------|----------------|------------|
| 0 | 10/27/2018 | UGV | $\approx 0.7m$ | 0° |
| 1 | 10/27/2018 | UGV | $\approx 0.7m$ | 0° |
| 2 | 03/08/2019 | UGV | $\approx 0.7m$ | 0° |
| 3 | 03/08/2019 | UAV | $\approx 2m$ | 20° |

4.1.3 NTU Dataset

Our NTU dataset is collected by multi hybrid robots consisting of a husky UGV platform and a UAV, recording driving around the carpark in front of School of EEE.

Our UGV platform is a HUSKY Clearpath robot, equipped with a ZED stereo camera $\times 1$, 672×376 , 87° HFoV, 56° VFoV. The picture of the platform and example images are shown in Figure 4.6 and 4.8.

The UAV platform is assembled with: PIXRACER V1.0 AUTOPILOT Controller Module, DJI E Series 620S Motor Package, a uBLOXNEO-M8N GPS Module and a monocular camera mounted at a depression angle of 20 degree. The overview picture of the UAV is shown in Figure 4.7

The dataset provides 4 rosbag files. 3 of them are recorded by UGV, while the other one is recorded by UAV. The basic information of 4 rosbags are listed in Table 4.2. And the ground truth trajectories are shown in Figure 4.5.

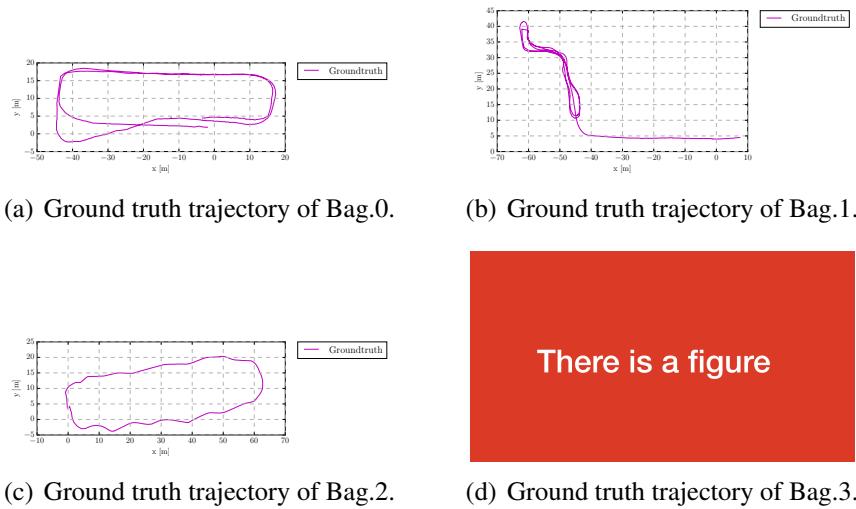


Figure 4.5: Comparison of images captured in the same location in different seasons in RobotCar dataset.



Figure 4.6: Overview picture of NTU Husky platform.



Figure 4.7: Overview picture of NTU Husky platform.



Figure 4.8: Example images of NTU dataset.

4.2 Evaluation of CORBSLAM

4.2.1 Evaluation on multi ground robots

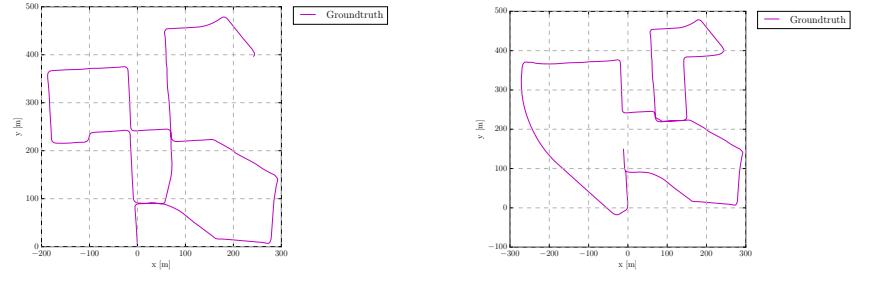
KITTI Datasets

In order to evaluate CORB-SLAM system, sequence 00 is utilized and separated into two sub sequences with proper length of overlap. The following separating method is employed: We assume the time period of a KITTI sequence if $Seq.0[0, t]$. Then the sequence is separated into two sub sequences $Seq.01[0, \frac{t}{2} + \delta t]$ and $Seq.02[\frac{t}{2}, t]$ as the assumed input of two client robots.

Therefore, in this case, Sequence 00 containing $f = 4541$ frames and covering a total distance of $s = 1856m$ is separated into two partial sequences: $Seq.0[0, \frac{2}{3}f]$ and $Seq.1[\frac{1}{3}f, f]$, both containing $\frac{2}{3}f \approx 3027$ frames and covering distances of $\frac{2}{3}s \approx 1237m$ (a rough estimate since distances between each pair of frames are not equal).

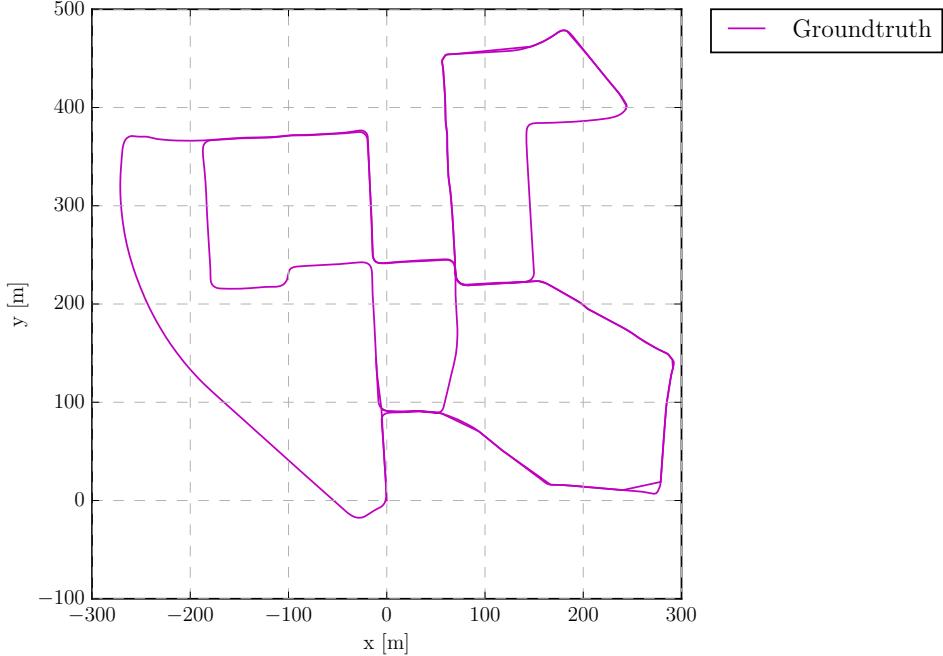
The ground truth information of Seq.0, Seq.1 and the complete ground truth trajectory of Sequence 00 are shown for reference in Figure 4.9. And Figure 4.12 demonstrates mapping results of each partial sequence and the map fusion results of the server. Four charts in Figure 4.13 contains quantitative evaluation results, with corresponding numeric results shown in Table 4.5.

Because the two partial sequences are extracted from Sequence 00, so the completed mapping results of CORB-SLAM client on Sequence 00 can be provided as a comparison by Figure 4.10, 4.11 and Table 4.3 in the same format as above. Results are further discussed in Section 5.1.



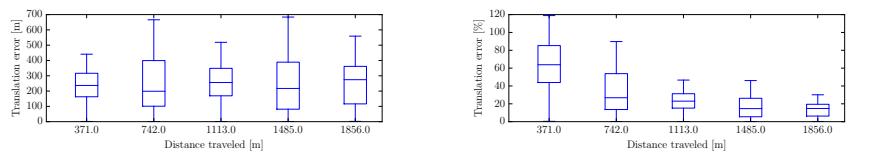
(a) Ground truth trajectory of Seq.0.

(b) Ground truth trajectory of Seq.1.



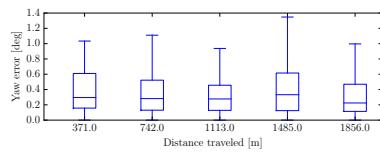
(c) Ground truth trajectory of complete Sequence 00.

Figure 4.9: Ground truth trajectory of partial and complete sequences of KITTI Datasets.

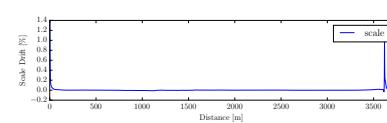


(a) Relative translation error.

(b) Relative translation error by percent.



(c) Relative yaw error.



(d) Scale error.

Figure 4.10: Quantitative evaluation results of CORB-SLAM client mapping the entire KITTI Sequence 00.

Table 4.3: Quantitative results of mapping unseparated Sequence 00.

| Distance(m) ¹ | Rel. Trans.(m) ² | Rel. Trans.(%) ³ | Rel. Yaw(deg) ⁴ | Scale Err. (%) ⁵ |
|--------------------------|-----------------------------|-----------------------------|----------------------------|-----------------------------|
| 371 | 229.69 | 61.91 | 0.37 | - |
| 742 | 260.10 | 35.05 | 0.37 | - |
| 1113 | 260.20 | 23.38 | 0.31 | - |
| 1485 | 240.93 | 16.22 | 0.40 | - |
| 1856 | 255.16 | 13.74 | 0.32 | - |
| - | - | - | - | 0.05 |

¹ Distance in meter traveled before each time of statistics.

² Mean relative translation error in meter.

³ Mean relative translation error in percent.

⁴ Mean relative yaw error in degree.

⁵ Median scale error in percent.

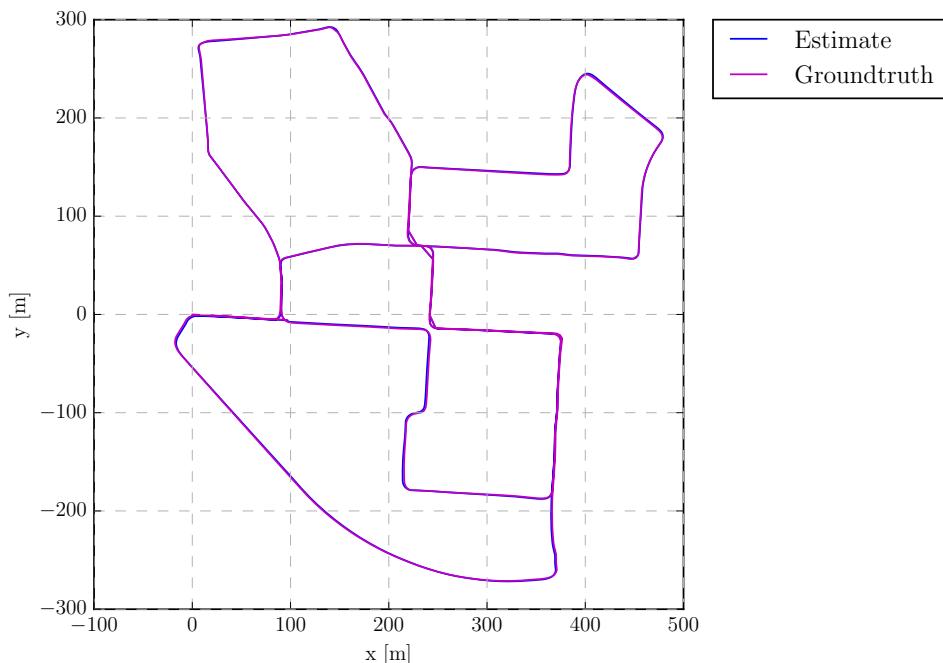
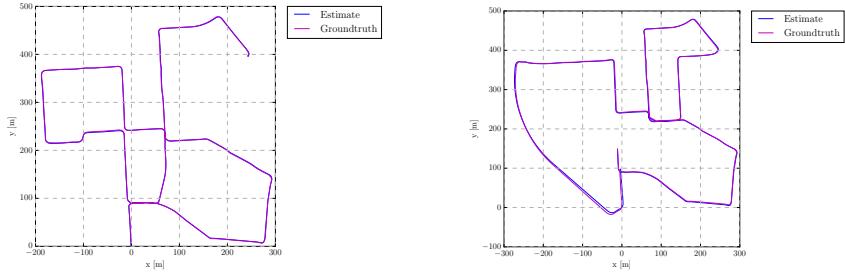


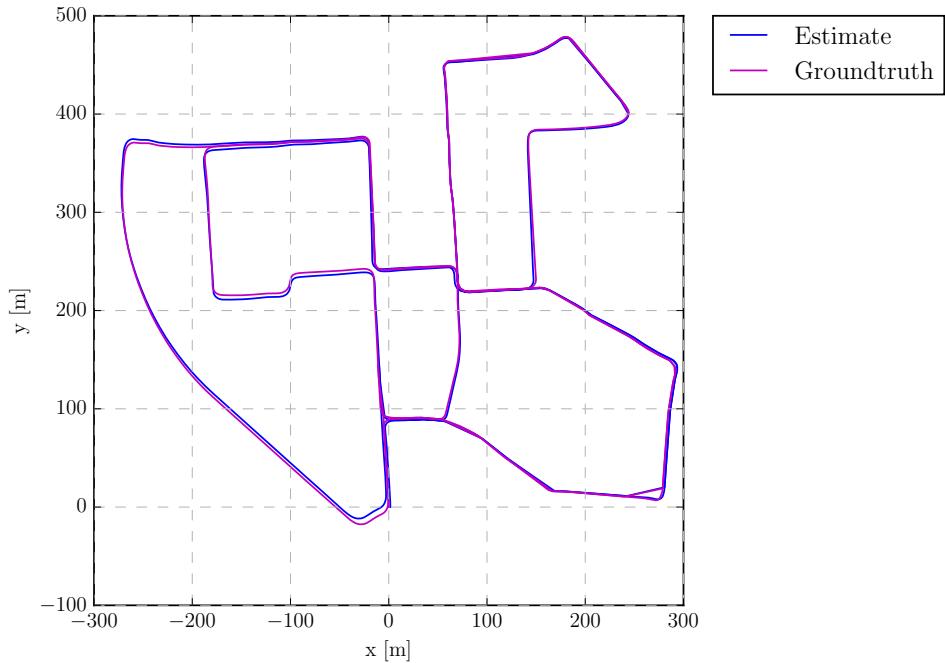
Figure 4.11: Mapping results of the entire sequence without partial sequence.

NTU Datasets

An obvious drawback of the evaluation on KITTI dataset is the images which are overlapped by two clients are exactly identical because they are extracted from the same sequence. Therefore, the results are expected to be much better than real-world applications in which case it is impossible the images recorded by different clients can be identical.



(a) Mapping result of Seq.0 compared with ground truth.
(b) Mapping result of Seq.1 compared with ground truth.



(c) Map Fusion results of Seq.0 and Seq.1 compared with ground truth.

Figure 4.12: Mapping results of Seq.0 and Seq.1, and the map fusion results of KITTI Datasets.

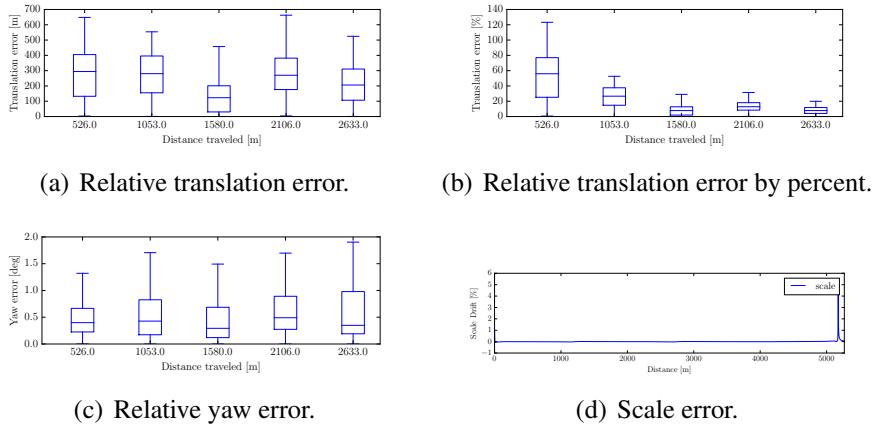


Figure 4.13: Quantitative evaluation results of fused map of KITTI Datasets.

Table 4.4: Quantitative results of map fusion evaluation on KITTI partial sequences.

| Distance(m) ¹ | Rel. Trans.(m) ² | Rel. Trans.(%) ³ | Rel. Yaw(deg) ⁴ | Scale Err. (%) ⁵ |
|--------------------------|-----------------------------|-----------------------------|----------------------------|-----------------------------|
| 526 | 283.40 | 53.88 | 0.46 | - |
| 1053 | 276.16 | 26.23 | 0.51 | - |
| 1580 | 153.74 | 9.73 | 0.48 | - |
| 2106 | 284.95 | 13.53 | 0.57 | - |
| 2633 | 219.66 | 8.34 | 0.54 | - |
| - | - | - | - | -0.15 |

¹ Distance in meter traveled before each time of statistics.

² Mean relative translation error in meter.

³ Mean relative translation error in percent.

⁴ Mean relative yaw error in degree.

⁵ Median scale error in percent.

Table 4.5: Quantitative results of evaluation on NTU Datasets.

| Distance(m) ¹ | Rel. Trans.(m) ² | Rel. Trans.(%) ³ | Rel. Yaw(deg) ⁴ | Scale Err. (%) ⁵ |
|--------------------------|-----------------------------|-----------------------------|----------------------------|-----------------------------|
| 54 | 39.38 | 72.93 | 44.39 | - |
| 109 | 44.88 | 41.18 | 57.01 | - |
| 163 | 26.09 | 16.00 | 32.12 | - |
| 218 | 54.99 | 25.23 | 46.11 | - |
| 272 | 64.66 | 23.77 | 54.65 | - |
| - | - | - | - | 0.10 |

¹ Distance in meter traveled before each time of statistics.

² Mean relative translation error in meter.

³ Mean relative translation error in percent.

⁴ Mean relative yaw error in degree.

⁵ Median scale error in percent.

In order to get more reliable and convincing evaluation results of CORB-SLAM system, another evaluation on multi ground robots is performed utilizing NTU Datasets. Bag.0 and Bag.1 described in Section 4.1.3 are selected in this test. These two bags recorded by two UGVs, have different starting and ending location, with limited overlapping, which is much more similar to the case of real-world applications. Clients' mapping results and map fusion results in the server end compared to ground truth trajectories are demonstrated in Figure 4.15. And ground truth information is provided in Figure 4.14 for reference. Quantitative results are represented in Figure 4.16 and Table 4.5. Results are further discussed in Section 5.1.

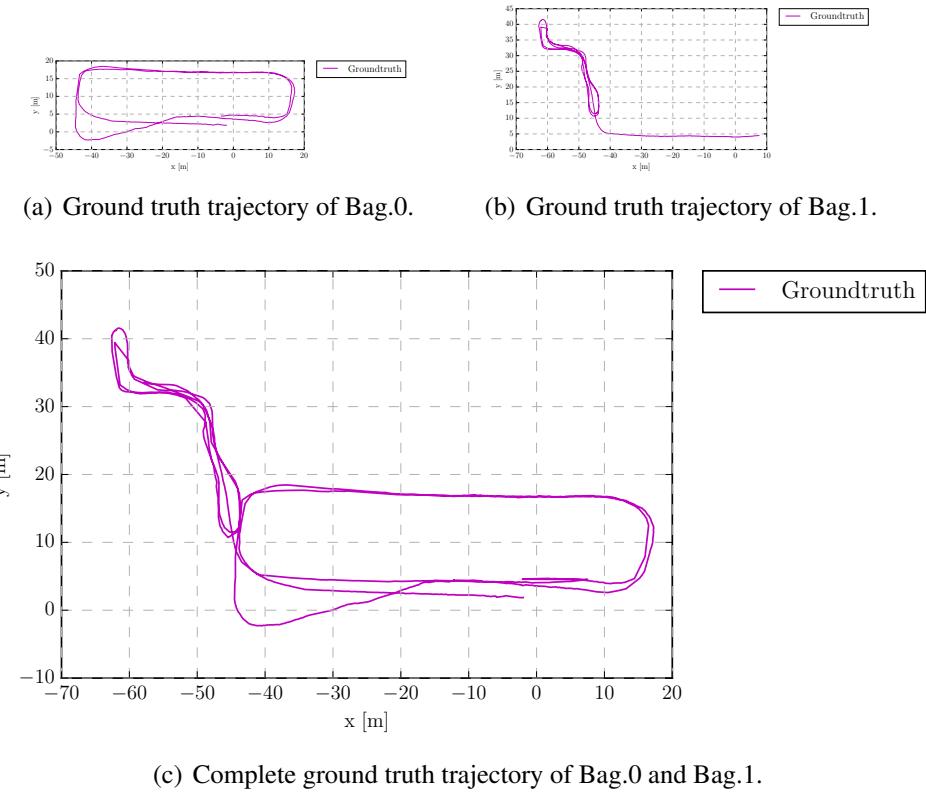


Figure 4.14: Ground truth trajectory of partial and complete bags of NTU Datasets.

4.2.2 Evaluation on multi hybrid robots

The evaluation of

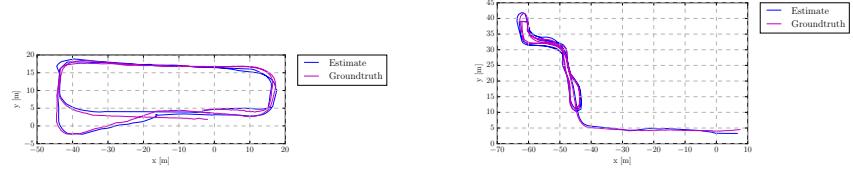
4.3 Evaluation under different illumination

Oxford RobotCar Datasets

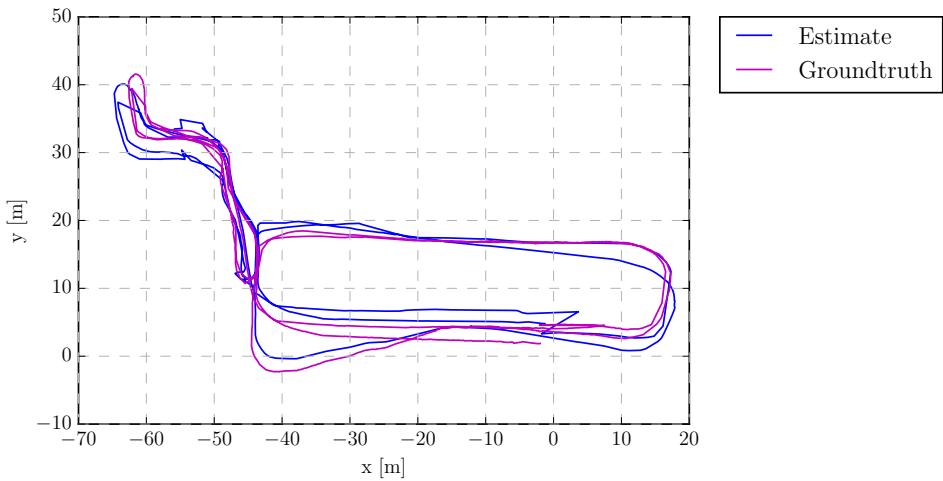
CORB-SLAM system integrated with illumination variance is firstly evaluated on the selected sequences of Oxford RobotCar Datasets, and then the mapping results are compared with the ground truth trajectories, with quantitative evaluation results calculated.

Two partial sequences are selected according the following principles:

1. Exclude the overexposed photo, which will cause tracking lost in ORBSLAM system. Because the dataset was collected in real-world outdoor street environment, there are some frames with overexposure e.g. Figure 4.17, which cannot be pro-



(a) Mapping result of Bag.0 compared with ground truth.
(b) Mapping result of Bag.1 compared with ground truth.



(c) Map Fusion results in server end of Bag.0 and Bag.1.

Figure 4.15: Mapping results of Bag.0 and Bag.1 and the map fusion result of server.

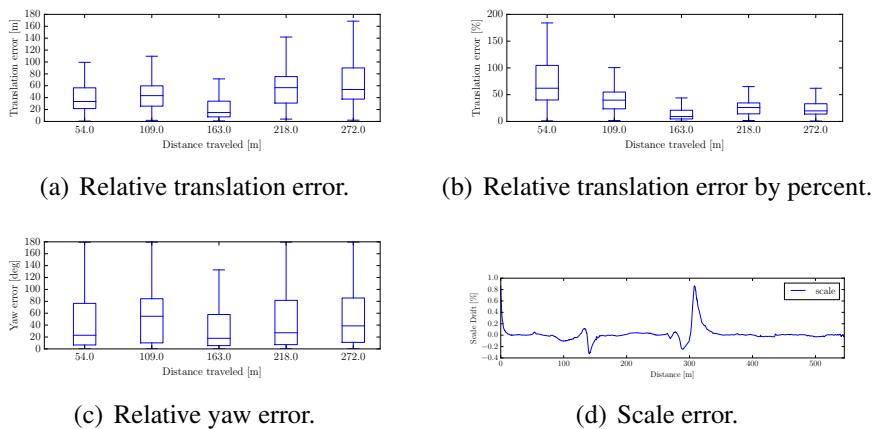


Figure 4.16: Quantitative evaluation results of fused map of NTU Datasets.

cess by vSLAM. Therefore, in this work, this dataset is intercepted into two subsequences excluding overexposed images.



Figure 4.17: Image sequence with overexposed frames in RobotCar dataset.

2. Avoid partial sequences where traffic congestion occurred. Because RobotCar Datasets are recorded in different hours during daytime, there are congestion starting at approximately 15:00, as shown in

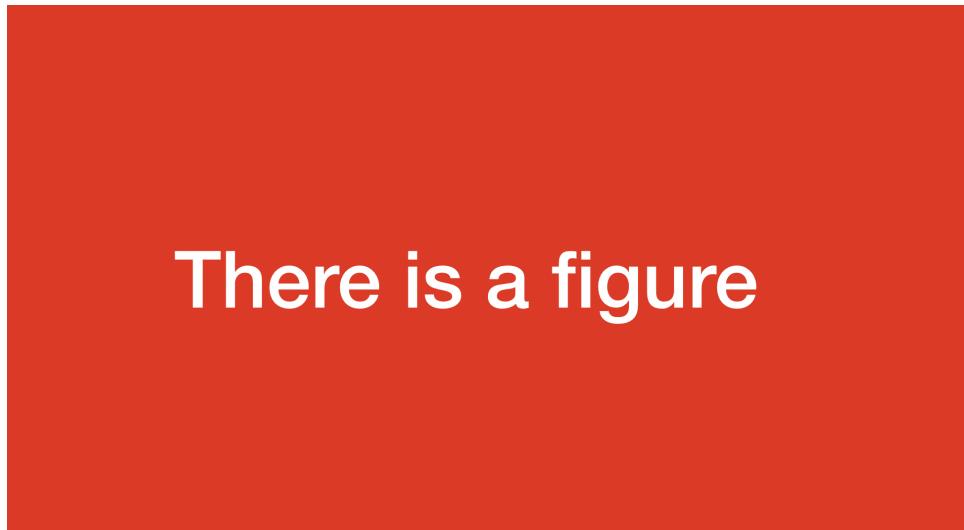


Figure 4.18: Images when traffic congestion occurred in RobotCar datasets.

3. Select partial sequence containing images with overlapping under different illumina-

Table 4.6: Partial datasets selected in RobotCar dataset.

| Seq. No. | Data(M/D/Y) | Time | Weather | Timestamps |
|----------|-------------|-------|-----------------|--------------------------------------|
| 0 | 07/14/2014 | 14:49 | summer overcast | 1405349847738682 to 1405350059147905 |
| 1 | 02/24/2014 | 12:32 | winter overcast | 1417794166325288 to 1417794407042717 |

nation conditions and in different season, as shown in Figure 4.4.

According to the above selection principles, the two sub sequences selected are listed in Table 4.6. The ground truth GPS/INS trajectories of two sub sequences and the combined overall trajectories are shown in Figure 4.19. The estimate trajectories and the fused map of two partial sequences are shown in Figure 4.20. Results of Oxford RobotCar Datasets are further discussed in Section 5.3.

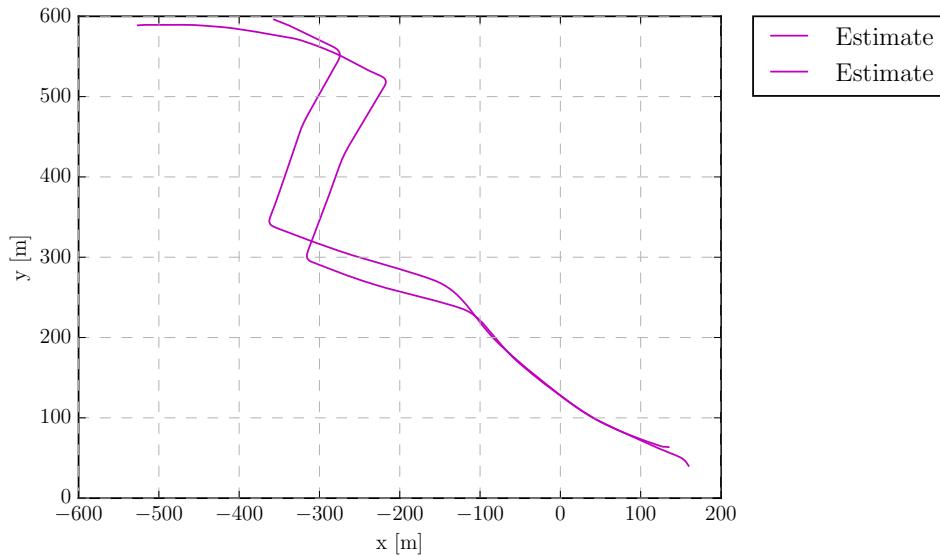
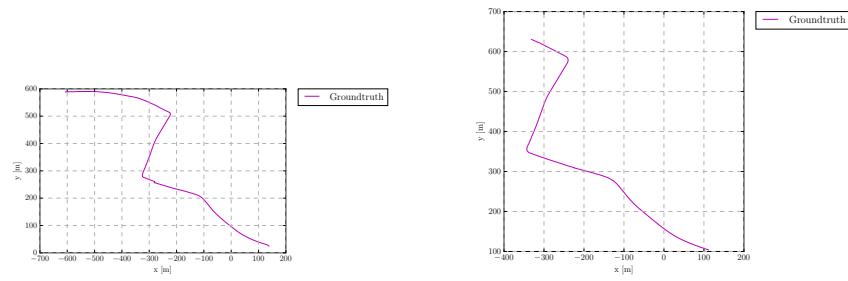
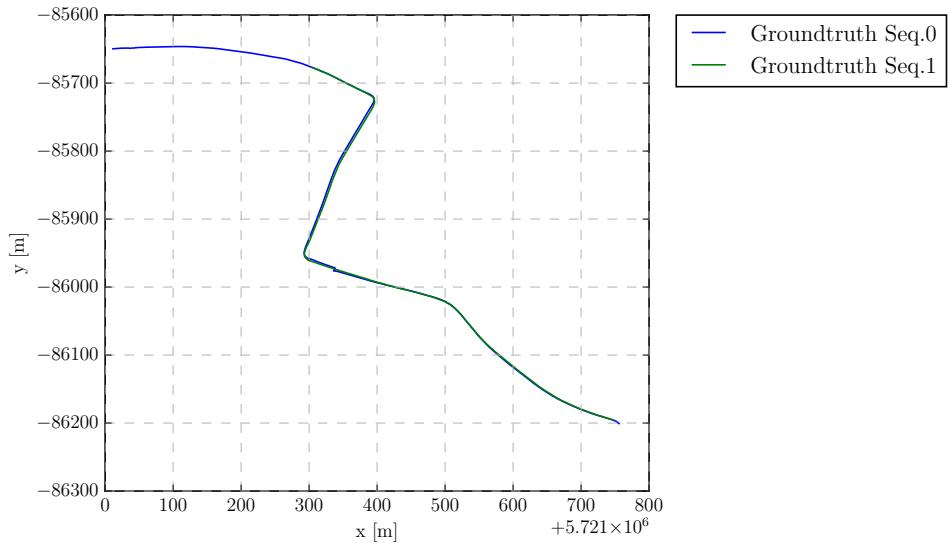


Figure 4.21: Map fusion results of Seq.0 and Seq.1 without ground truth in Oxford RobotCar Datasets.



(a) Ground truth trajectory of Seq.0. (b) Ground truth trajectory of Seq.0.



(c) Overall ground truth trajectory of Seq.0 and Seq.1.

Figure 4.19: Ground truth individual and overall trajectories of Seq.0 and Seq.1 in Oxford RobotCar Datasets.

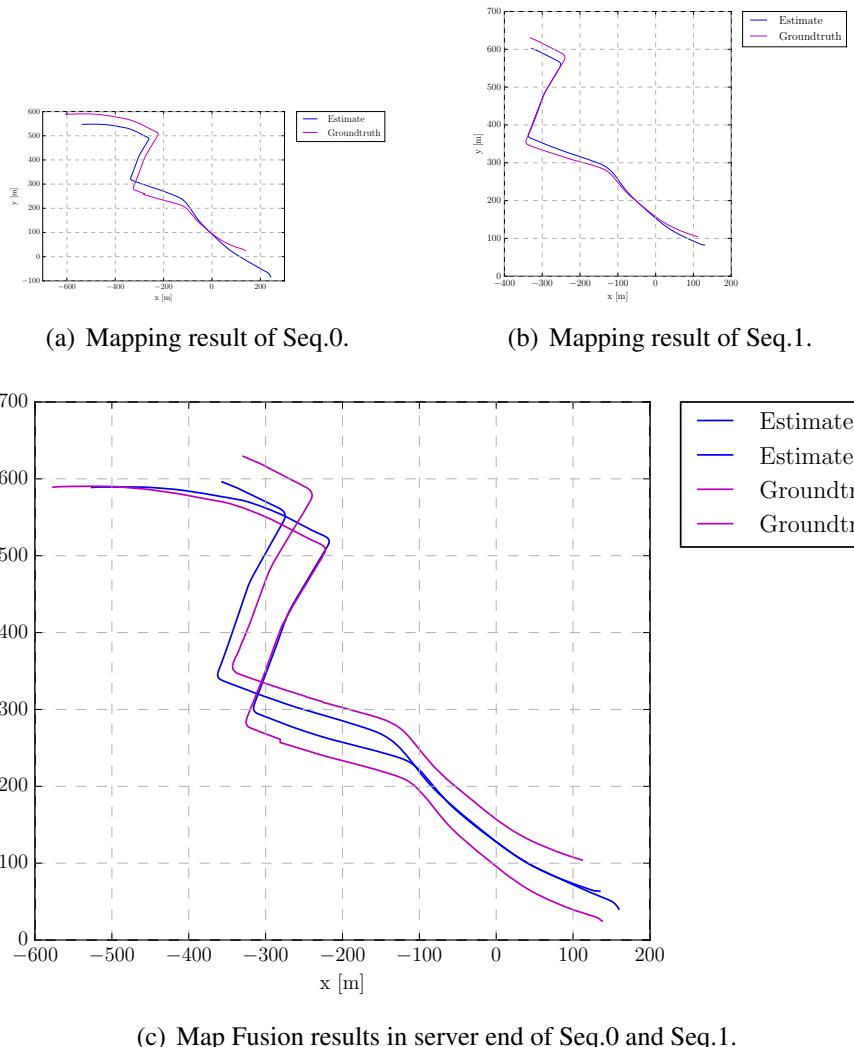


Figure 4.20: Mapping results of Seq.0 and Seq.1 and the map fusion result of server in Oxford RobotCar Datasets.

Chapter 5

Discussion

5.1 Results of multi ground robots cluster

Seen graphically according to Figure 4.12, the mapping results of CORB-SLAM clients is able to match the ground truth trajectory fairly well enough. And seeing the numeric analysis in Table 4.4, the completed map fused by the server has 8.34% mean relative translation error and 0.54° mean relative yaw error with all distance traveled.

Comparing the fused map with the mapping results on the original unseparated sequence, according to the differences between Table 4.4 and 4.3, map fusion in CORB-SLAM server slight reduces the accuracy on relative yaw and scaling. However from the table, the relative translation accuracy is numerically increased, of which a critical reason is the distance traveled by each client is inevitable shortened because the sequence is divided into two parts, which means translation errors on each client are accumulated during shorter distances. Therefore, it is not concluded so far that map fusion module in server can increase accuracy of relative translation.

5.2 Results of multi hybrid robots cluster

5.3 Failure Reasons and Drawbacks of Illumination Variance Method

According to the ground truth information of the selected partial sequences of Oxford RobotCar Datasets, the correct fused estimate trajectories of clients should be coincident with very little offset seen as Figure 4.19. However as shown in Figure 4.21, integrating CORB-SLAM system with illumination variance failed to enhance the ability to deal with illumination and season changes in Oxford RobotCar Datasets.

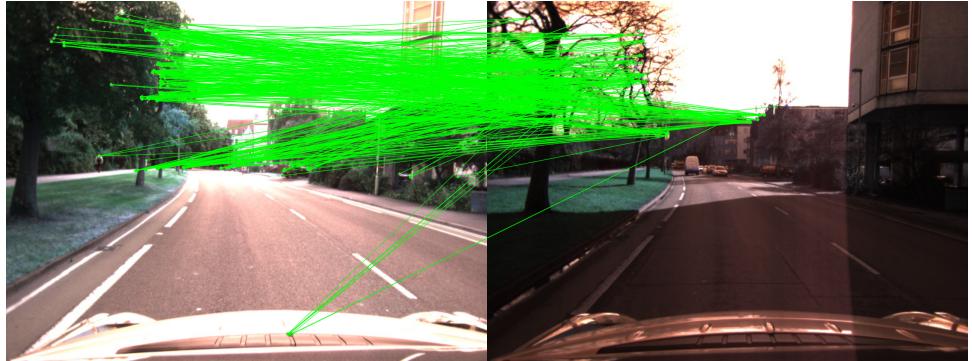
As seen in Figure 4.21, illumination variance method introduce many incorrect matches of keypoints while it is expected to allow ORB matcher to find more correct keypoint pairs that hard to match in raw images due to illumination changes.

By analyzing the basic formula to compute illumination variance, Equation 2.1 which is repeated below as Equation 5.1 for reference, and the result images in Figure 5.1, the following reasons and drawbacks of illumination variance method can be concluded to explain the failure of it to help CORB-SLAM deal with images under different illumination conditions and seasons:

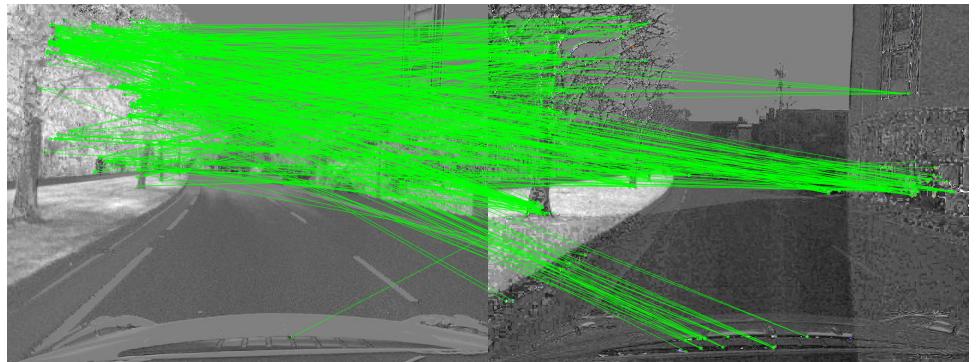
$$I = \log(G) - \alpha \log(B) - (1 - \alpha) \log(R) \quad (5.1)$$

1. Loss of resolution. According to the computation shown in Equation 5.1, there are two steps in this method to calculate the value of illumination variance: for each pixel, 1) logarithm of r,g, b channel values, 2) take their weighted difference as the result illumination variance value. Both steps cause serious loss of resolution, with the result image very blurry as seen in Figure 5.1.
2. Requirement of high brightness and contrast of input color images. In Figure 5.1, compared to Figure 5.1(a), Figure 5.1(a) has a higher resolution. This is because with the loss of resolution during the illumination variance computation, images with higher brightness and contrast can remain more details in the result images. But the background of application of this method is in life-long localization and

mapping system, running under significant lighting and season conditions, which means it is an unreasonable request to demand the input images always bright and sharp.



(a) Corresponding matched keypoint pairs of raw images Figure 4.4(a) and 4.4(b).



(b) Corresponding matched keypoint pairs of illumination variance images Figure 5.1(a) and 5.1(b).

Figure 5.2: ORB Keypoint matching results of raw and illumination variance images in Oxford RobotCar Datasets.

However, in both the original work [34] and the related implement in [36–39], the application of this method only focus on localization, which means the main function is designed to detect loop closures in images taken in different illumination and seasons, but not suitable for mapping. In all above papers, evaluation results are given only by localization results.

A critical difference of localization and mapping tasks is high resolution images are not necessary in localization, while in mapping task they are. Cited by [37], [44] explains that performing localization using a sequence of images rather than single image removes the requirement that the image matching scheme be able to reliably calculate a single global image match. However, without the functionality of calculat-



(a) Corresponding illumination variance image of Figure 4.4(a).



(b) Corresponding illumination variance image of Figure 4.4(b).

Figure 5.1: Generated illumination variance images of example raw images in Oxford RobotCar Datasets.

ing matches between single images, sequence-based image matching algorithms have significant drawbacks that cannot calculate the transformation between images.

And in the case of CORB-SLAM, the image matching algorithm combining ORB keypoint and Bag of Words, is able to calculate matching and transformation between individual images, but fit not well with illumination variance method.

Chapter 6

Conclusion and Recommendations

6.1 One

6.2 Two

6.3 Three

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Appendix A

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Appendix B

(Code Here)