Place Recognition and Localization for Multi-Robot SLAM

Liu Xiangyu

SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING

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Abstract

Abstract goes here.

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Keywords: Dissertation, keywords.

Acknowledgement

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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 [1]:

- 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.

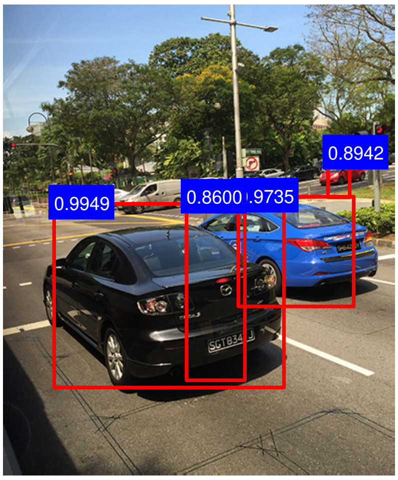

Figure 1.1: TBD

1.2 Motivation and Objectives

Recently, some solutions for Multi-robot SLAM systems have been proposed. [2]

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 [3].

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 three 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.

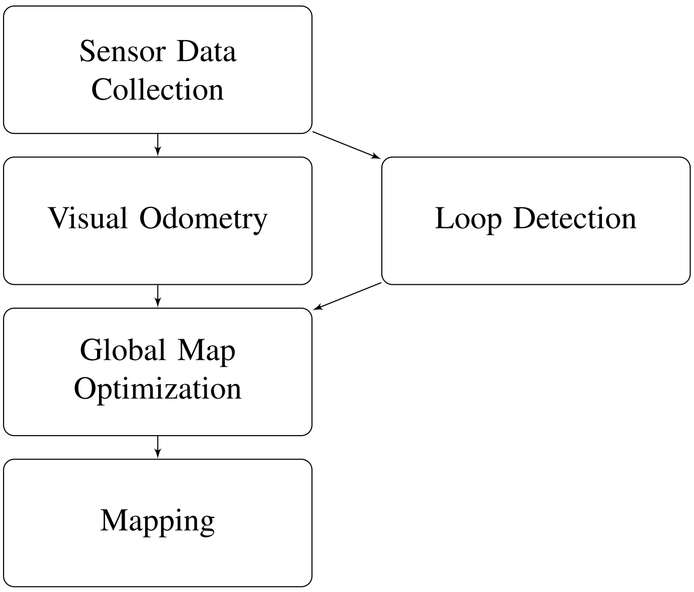

Figure 2.1: Classic structure of Visual SLAM

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, the reconstrcuted 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 [4, 5].

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 Algorithms

2.2 Visual SLAM Solutions

2.2.1 ORB-SLAM

[6] [7]

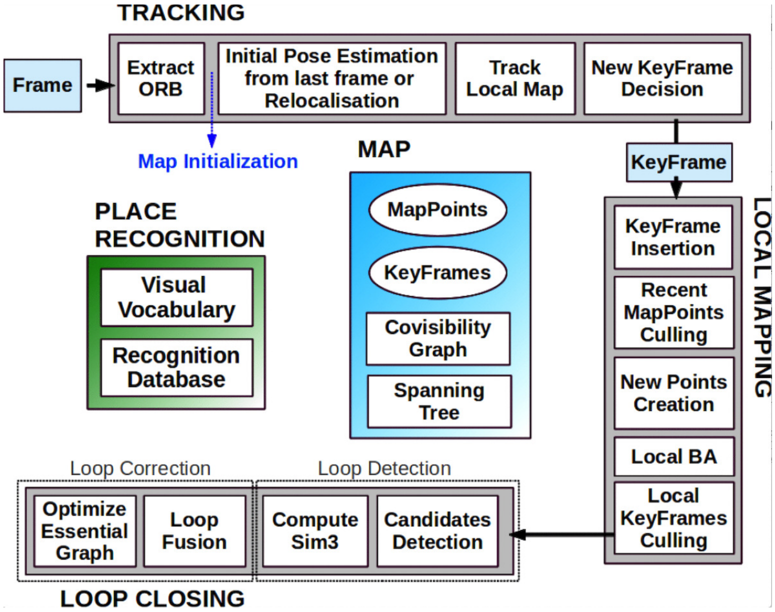

Figure 2.2: ORB-SLAM system overview.

2.2.2 CORB-SLAM

[8]

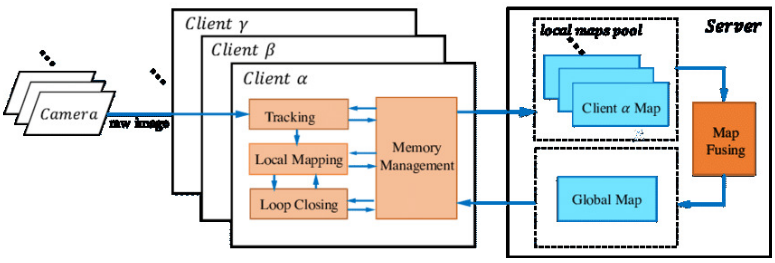

Figure 2.3: The framework of CORB-SLAM system.

2.3 Shade Dealing Algorithms

2.3.1 Model-based Approaches

2.3.2 Illumination Variance

Model-based shade dealing approaches can remove shade more precise, with fewer image details lost, however, obviously their disadvantages limits their application.

Model-based approaches requires the type and position of light sources as a prior information to model the illumination patterns, which process has high computational complexity. But vSLAM systems have significant computational cost already, usually deployed on platforms with limited computation capacity, and in most of cases, vSLAM runs in an indoor or outdoor real-world environment with information of light sources unknown. Therefore, these two disadvantage determine model-based approaches are not suitable to be combined with vSLAM.

In the case of vSLAM, considering the requirement of low computational complexity and lower image resolution is acceptable, a simpler approach without modeling is preferred.

Illumination variance approach proposed in [9], is a simple method based on only one equation computing illumination variant images.

[2] [10]

$$R^{x,E} = \tag{2.1}$$

$$I = \log(R_2) - \alpha \log(R_1) - (1-\alpha)\log(R_3) \tag{2.2}$$

2.3.3 Life-Long SLAM

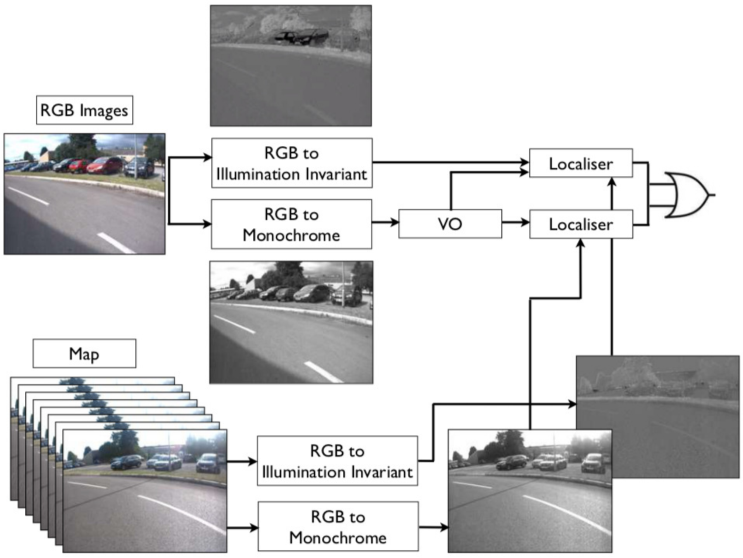

Figure 2.4: Block-flow diagram of the combined stereo localisation approach.

Chapter 3

Approach (Actual work done and contribution, including literature survey)

3.1 Evaluation of CORBSLAM

3.2 Modification to CORBSLAM

3.3 CORBSLAM with Illumination Variance

Chapter 4

Test and Experiments

4.1 Evaluation of CORBSLAM

4.1.1 Evaluation on multi ground robots

4.1.2 Evaluation on multi hybrid robots

4.2 Evaluation under different illumination

Chapter 5

Discussion

5.1 One

5.2 Two

5.3 Three

Chapter 6

Conclusion and Recommendations

6.1 One

6.2 Two

6.3 Three

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Appendix A

(Code Here)

Appendix B

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