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# Keyframe-based Visual-Inertial Odometry for Small Workspace

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**Xi Li**

angefertigt unter der Leitung von / supervised by  
DR. ROLAND ANGST

betreut von / advised by  
DR. ROLAND ANGST

begutachtet von / reviewers  
DR. ROLAND ANGST  
PROF. DR. ANTONIO KRÜGER

Saarbrücken, June 2016

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# Keyframe-based Visual-Inertial Odometry for Small Workspace

by  
Xi Li

Submitted to the Department of Computer Science  
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Master of Science in Computer Science

## **Abstract**

Thesis Supervisor: Roland Angst  
Title: Dr.



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# Chapter 1

## Introduction

In past few years, the development of *Robotics* has surpassed people's expectation. The word *Robotics* has been first appeared in science fiction "Liar!" by Issac Asimov [27], it referred to science and technology of robots. By definition, *Robotics* is a research branch that related to design, control and application of robots, as well as processing feedback from robots.

Modern robots have been classified into several categories(e.g., Mobile robot, industrial robot, service robot, education robot etc.) with their usages. Among those categories, full-autonomous or semi-autonomous mobile robots attracts more and more researches. Such robots have abilities to move around in their moving space, with or without humans' control. The aim of research in mobile robots is to help us accomplish various hard tasks, whether domestically, commercially or militarily. These tasks, such as assisting disabled people, defusing bombs, or repair equipment in dangerous place is either risky or high expense for human beings.

For mobile robot, finding physical location of itself in unknown environment is normally crucial, such an ability(e.g., *Robot Navigation*) allows mobile robots avoid risky obstacles and finally arrive the goal position. Roughly speaking, *Robot Navigation* is a computing system which processes the information from external sources(e.g., sensors) and apply an algorithm to navigate robot, and sometimes build a map of environment. In *Robot Navigation*, robots sense environmental information by their sensors. These sensors, either locally (e.g., camera, inertial measurement unit (IMU)), or globally (e.g., Global Positioning System) detect events or changes in environment, and transfer their data to robots. Generally, sensors equipped in mobile robot (Local Sensor) are designed light, small, and inexpensive considering convenient movement and low expense. Camera and IMU sensor are considered most common local sensor in small mobile robot system.

A camera is a optical instrument for capturing images. Modern camera has several advantages for *Robot Navigation*. First, the core of camera chip set is cheap and easily installed in any mobile robot system; Second, camera often brings very rich information as it simulates the functioning of human eye. By recognizing key-points [24, 18, 23] in certain images, system observes the *landmarks* in environment, and those *landmarks* will localize robots by *Triangulation* [4, 14, 6].

A IMU sensor (Figure 1-1) often combines *gyroscope* and *accelerometer*, sometimes





Figure 1-1: IMU sensor with gyroscope and accelerometer measures rotational rate and acceleration of X, Y, Z axis regarding its local frame. Note that IMU sensor normally has bias and irreducible noises, it is necessary to apply a calibration like cameras. The frequency of IMU output is normally larger than 100 Hz. Source: [1]

*magnetometer*, to measure specific force, angular rate and magnetic field regarding to its local frame. IMU is one of main component in *Inertial Navigation System*, which firstly used in air plane, spacecraft, guided missiles, and now also in mobile robot [2, 15, 20, 8]. IMU sensor utilize *Dead Reckoning* to track device's position, such technology tries to integrate IMU data over time by assuming the movement model of devices fixed(i.e., acceleration and rotation rate is constant over small period of time).

## 1.1 Motivation and Contribution

The main motivation of this thesis is to improve the navigation accuracy by fusing camera data and IMU sensor data.

Single sensor-based navigation system may not satisfy the requirements of high-quality localization by mobile robot. GPS-based navigation system has been used for outdoor devices for long time. However, such a system suffered from localizing in indoor environment, and also the accuracy of general GPS is not high, i.e., 3 to 5 meters error [26]. For mobile robot, which may move from in-door to out-door, and requires high-accuracy navigation, GPS is mostly not used, or as baseline of navigation [12].

Vision-based navigation system [4, 14], or simultaneous localization and mapping (SLAM) [5, 7, 21] gives an acceptable navigation result. [4] recognizes corner feature by single camera, and it uses a extended kalman filter framework to track the uncertainty and propagates the system state, however it can not handle large-scale scene. [14] utilizes key-frame based bundle adjustment to update the map, improves both

accuracy and efficiency, it still met some problem in large-scale scene, because vision-based method often is a trade-off between computational complexity and localization accuracy due to the rich information and low output frequency by camera.

Single *Inertial Navigation System* recognize its pose by *Dead Reckoning* [19, 16]. However, the problem of *Dead Reckoning* error accumulation; Only few directions are observable [12] by IMU during whole navigation process. When object corrupts movement assumption, a correction step by external data will be needed.

Fusing camera and IMU data has many advantages. On the one hand, it can decrease computational time by making good use of high-frequency IMU data; On the other hand, it can reduce the error accumulation of IMU integration by the correction of vision-based navigation result within several turn. Fuse the camera and IMU data for robot navigation is not novel. [20] applies multi-state kalman filter (MSCKF) on state update, decrease the computational complexity by only keeping few last information of keyframe. [12] analysis the consistency of MSCKF, correct the ways of IMU integration to obtain consistency of system, therefore increase the accuracy. [8] exploits a way to optimize manifold information, therefore solving data fusing problem in a non-linear optimization scheme. Unfortunately, codes and data of above methods are not accessible, that motivates to explore possible methods to increase accuracy of *vision-inertial navigation system* both theoretically and experimentally.

The contributions of this thesis are as follows,

- We exploit a highly flexible, realistic software to generate synthetic IMU sensor data and corresponding vision data, that is the main source to provide experimental data in this thesis.
- We present error-state kalman filter system kinematic based on quaternion, explore the multiple ways to integrate IMU data due to different movement models.
- We propose a novel method to update fusing result based on key-framed bundle adjustment.
- We propose a real-time visual-inertial framework implemented in C++, which is stable, scalable, high-accuracy and low-latency.

## 1.2 Outline of the Thesis

In Chapter 2 we first overview our visual-inertial odometry, including world representation, important notations, we also compare filter method and key-frame based method in SLAM problem, and in the end we explain our choice in this thesis.

Then we enter the Chapter 3, which introduces *Quaternion Algebra*. In this chapter, we introduces the basic operations on quaternion, the relationship among quaternion, rotation matrix and rotation vector. In this chapter, we also explain how to integrate or derivative quaternion over time.

Chapter 4 is main part of this thesis. In Section 4.1, we study the Error-State Kalman Filter (ESKF), and apply it to IMU integration; Section 4.2 we summarize

how to fuse camera into ESKF, and how to optimize it by key-frame based bundle adjustment. In Section 4.3, we overview the pipeline of our visual-inertial odometry system.

We show our experiment results in Chapter 5. First, the process of generating synthetic IMU and camera data is presented. Then we run several experiments to show our proposed visual-inertial odometry has higher accuracy than single IMU integration, visual SLAM, as our system is still running in real-time.

In the end, we summarize and discuss our work and analysis the potential future work in Chapter 6.

# Chapter 2

## Overview of Visual-inertial Odometry

In this chapter, we will overview visual-inertial odometry system. In section 2.1, we will introduce world representation(e.g., world frame, camera frame and IMU frame) together with basic notations in our odometry system. Then in section 2.2, we will discuss two important scheme, filter method and keyframe Bundle Adjustment(keyframe BA) in SLAM algorithm, and explain why we finally choose keyframe-based method.

### 2.1 World Representations and Notations

Visual-inertial odometry [17], literally, is an odometry system, which received environment information by visual (camera) and inertial (IMU) sensor. VIO is similar with well-known visual odometry (VO) problem [22], with an additional IMU sensor, it tries to estimate agent's pose as agent keep moving in the environment. One big difference between VIO and SLAM algorithm is that VIO does not or only build a simple map, whereas SLAM normally maintains and continuously updates a map.

To setup a VIO system, we need to first define the ways to represent the world. Globally, we have a world frame  $\mathcal{W}$ ; World frame  $\mathcal{W}$  is set to a right-handed Cartesian coordinate system that every objects has an absolute pose (translation and rotation) in it. Then we have local frame for each sensor, i.e., IMU frame  $\mathcal{I}$  and camera frame  $\mathcal{C}$ ; Every time camera and IMU sensor obtain observations within their own local frame, we need to integrate those data and estimate the pose of those sensors in world frame  $\mathcal{W}$ . Figure 2-1 shows the overall world representations. Both IMU frame and Camera frame are right-handed Cartesian coordinate system.

In this master thesis, we use following notations,

- We denote scalars as  $a, b, c$ , vectors as  $\mathbf{a}, \mathbf{b}, \mathbf{c}$ , matrices as  $\mathbf{A}, \mathbf{B}, \mathbf{C}$ , frames as  $\mathcal{A}, \mathcal{B}, \mathcal{C}$ .
- We denote measurement  $\mathbf{m}$  in particular frame  $\mathcal{F}$  as  $\mathbf{m}_{\mathcal{F}}$ . To further simplify, any parameter that is **not** in world frame shall be denoted particularly. For example, the translation  $\mathbf{p}$  in camera frame will be denoted as  $\mathbf{p}_{\mathcal{C}}$ , and the translation  $\mathbf{p}$  in world frame will be denoted as  $\mathbf{p}$ .

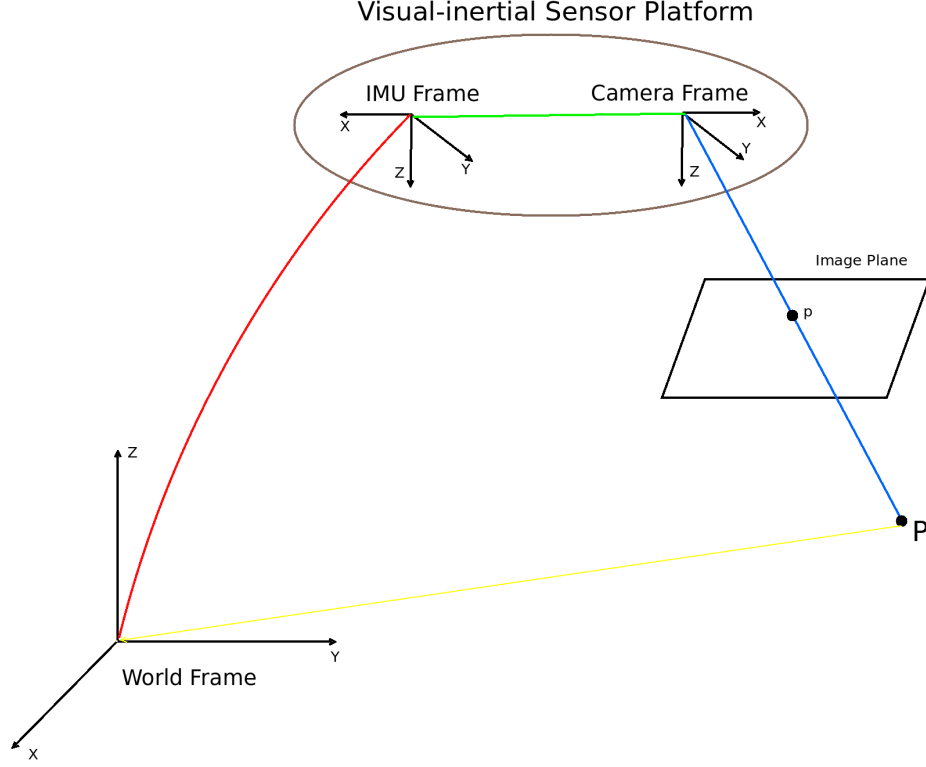


Figure 2-1: This figure shows the connection among world frame  $\mathcal{W}$ , IMU frame  $\mathcal{I}$  and camera frame  $\mathcal{C}$ . Green line shows the transformation between camera and IMU, which can be pre-calibrated. Red line is the pose of IMU in world frame. Camera frame observes point  $\mathbf{p}$  of object  $P$  in image plane, and connects a object  $P$  by blue line, and the coordinate of object  $P$  in world frame is presented as yellow line.

- A general translation  $\mathbf{t}$  should express a translation from point  $A$  to point  $B$  in frame  $\mathcal{C}$ , which is denoted as  $\mathbf{t}_C^{AB}$ . We simplify a point  $\mathbf{p}$  in frame  $\mathcal{A}$  as  $\mathbf{p}_A$ , when this point is the translation  $\mathbf{t}_A^{OP}$ ,  $O$  is origin of frame  $\mathcal{A}$ , and  $\mathbf{p} = P$ , this holds same for vector.
- A general rotation is either expressed in quaternion  $\mathbf{q}$  or rotation matrix  $\mathbf{R}$ . We use quaternion  $\mathbf{q}$  as example. A quaternion is a orientation operation from frame  $\mathcal{B}$  to frame  $\mathcal{A}$ , and it is denoted as  $\mathbf{q}_{AB}$  in this thesis. Noted that if such a operation is from world frame  $\mathcal{W}$  to some frame  $\mathcal{B}$ , we omit both frame for simplification, i.e.,  $\mathbf{q}_{WB} \triangleq \mathbf{q}$ .

## 2.2 Filter Versus Keyframe

It is important to note that though this thesis focus on visual-inertial odometry for small workspace, we still tend to keep the possibility to extend our system to a general, scalable and efficient SLAM system. SLAM system usually have two parallel process, one is for localization and the other is for mapping, the crucial point of building such

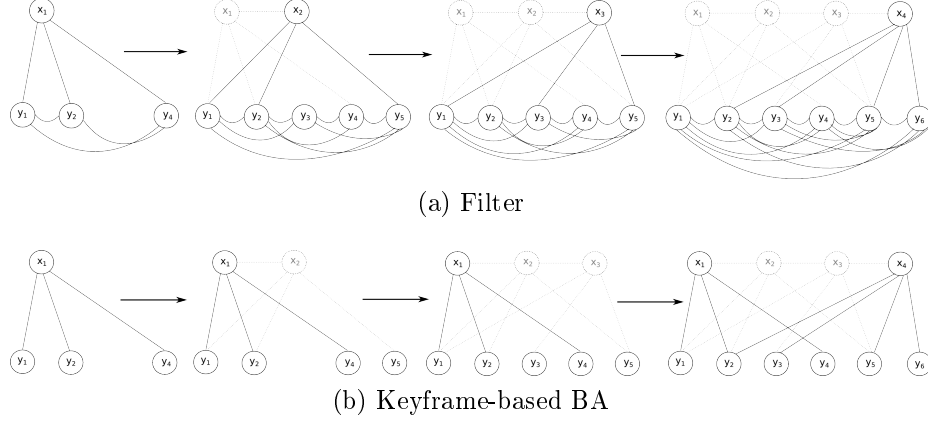


Figure 2-2: (a) Filter method for SLAM. (b) Keyframe-based Bundle Adjustment (BA) for SLAM. We denote the  $i^{th}$  camera position as  $\mathbf{x}_i$ ,  $i^{th}$  image feature as  $\mathbf{y}_i$ . We connect the line between camera and image feature if this feature is observed by this camera, the vanished observations is presented as dotted line, and the vanished camera is expressed as grey font. Both graph changes as time goes on from left to right. One can see from (a) that though only the latest camera pose is reserved, the edges between features are increasing exponentially. (b) stores some of former camera poses (keyframe) (i.e.,  $\mathbf{x}_1$  and  $\mathbf{x}_4$ ) by keeping graph stay sparsity.

a system is to keep both processes efficient. There are two general framework (e.g., filter-based method and keyframe-based method) in SLAM. In this section, we want to discuss whether filter-based method or keyframe-based method are more suitable for our case.

Filter-based SLAM [5, 6, 4] uses *Extended Kalman Filter* (EKF) to propagate state and update the covariance of the state. In each step, system obtain the current pose estimation and map update by marginalising all former information. This marginalising step usually eliminates the former pose and adds connections to image features. As showed in Figure 2-2a, the graph will not grow fast with time since the former pose has been eliminated and features in environment is limited. However, once the system moves to large scale scene, the problem of limiting the number of features become severe as the graph tends to be fully-connected.

Keyframe-based SLAM [14, 20, 9, 7, 21] applies *bundle adjustment* (BA) for keyframes to update the map in each step. In keyframe-based SLAM, it stores some historical poses (keyframes), and combines with image feature points to do a BA step. The chosen of keyframes varies from implementations, the idea is to pick up the poses that is not very close to last keyframe, otherwise the information might be redundant, which might lead to increase the computational cost. In Figure 2-2b, the graph still stays sparsity as the number of poses and features increases. The drawback might be the behaviour of pose estimation is inadequate as it ignores some of former information.

In [25], they conclude that keyframe-based SLAM is slightly better than filter-based SLAM in their experiment settings, especially when scale of scene becomes larger. In this master thesis, we choose keyframe-based method for visual part and

filter method for IMU integration part. We choose filter method for IMU integration part is that we do not keep former information (e.g., image features or landmarks) in integration step, hence each filter step can be regarded as an optimization step. The reason why we use keyframe-based method for visual part is that we want keep the scalability of our system, besides the results from IMU integration can be a good compensation in case of the lack of pose estimation in keyframe-based BA.

# Chapter 3

## Background on Quaternion Algebra

One important task for this master thesis is to integrate IMU data over time to estimate camera pose (e.g., position and orientation). By assuming movement model, it is straightforward to integrate position in Cartesian space, however integrating orientation in manifold space is often not a easy task. In this chapter, we introduce the quaternion algebra, and explore the way to operate quaternion over time.

### 3.1 Definition of Quaternion

A quaternion  $Q$  is defined as,

$$Q = q_w + q_x i + q_y j + q_z k \quad (3.1)$$

where  $\{q_w, q_x, q_y, q_z\} \in \mathbb{R}$ , and  $\{i, j, k\}$  are three imaginary unit length, e.g.,  $i^2 = j^2 = k^2 = ijk = -1$ .

In most cases, we represent quaternion  $Q$  as a four-element vector  $\mathbf{q}$  composed by above four real number  $\{q_w, q_x, q_y, q_z\}$ , i.e.,

$$\mathbf{q} \triangleq [q_w \ \mathbf{q}_v] = [q_w \ q_x \ q_y \ q_z]^T \quad (3.2)$$

where  $q_w$  is the real part of  $\mathbf{q}$ , and  $q_v$  is a 3-vector to represent imaginary part of  $\mathbf{q}$ .

It is worth to be noted that there are two different conventions of quaternion  $\mathbf{q}$ , *Hamilton way* [11] and *JPL way* [3]. In Hamilton convention, the real part  $q_w$  is the first component of  $\mathbf{q}$ , i.e.,  $[q_w \ \mathbf{q}_v]$ , whereas in JPL way, the real part is the fourth component, i.e.,  $[\mathbf{q}_v \ q_w]$ . To avoid confusions, and considering Hamilton way is more common to use, especially for implementation [10, 13], we hereby claim that we use **Hamilton way** to represent quaternion  $\mathbf{q}$  throughout this master thesis.



### 3.2 Properties of Quaternion

### 3.3 Quaternions and Rotation operations

### 3.4 Time-derivatives and Time-integration on Quaternion

# Chapter 4

## Modular Sensor Fusing

### 4.1 Error-state Kalman Filter for IMU Integration

#### 4.1.1 Motivation

#### 4.1.2 System Kinematics

#### 4.1.3 State Propagations

#### 4.1.4 State Reset

### 4.2 Camera as Complementary Sensory Data

#### 4.2.1 Motivation

#### 4.2.2 Self-adapt Map Scale

#### 4.2.3 Keyframe-based Bundle Adjustment

### 4.3 Visual-inertial Odometry Pipeline Overview

# Chapter 5

## Experiments

### 5.1 Synthetic Dataset

### 5.2 Some other experiments

## Chapter 6

# Summary, Discussion and Future Works

# Appendix A

## Integration Methods

### A.1 Runge-Kutta Numerical Integration Methods

### A.2 Closed-form Integration Methods

# Appendix B

## Approximation Methods

[20]

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