Institutionen för datavetenskap
Department of Computer and Information Science

Master's Thesis

Autonomous UAV Landing Using Monocular Vision in GPS-denied Environments

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Sammanfattning
Abstract

This thesis treats the subject of landing a quadrocopter autonomously.

Traditionally this, and most advanced UAV control, has been approached using off-board cameras and sensors to get a precise pose estimation. This however restricts the utility of the controlled UAV's to a very limited space where sophisticated and expensive gear is available and properly configured. By using only on-board sensors, not only is the utility of the UAV greatly increased, but costs are also cut.

To assist the positioning the quadrotor is equipped with a camera utilized by a library for monocular SLAM.

Nyckelord
Keywords automated landing, slam, ptam, control, uav

Abstract

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Traditionally this, and most advanced UAV control, has been approached using off-board cameras and sensors to get a precise pose estimation. This however restricts the utility of the controlled UAV's to a very limited space where sophisticated and expensive gear is available and properly configured. By using only on-board sensors, not only is the utility of the UAV greatly increased, but costs are also cut.

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Sammanfattning

Svenskt abstract kan man placera här.

Acknowledgments

Till mor och far

Contents

Chapter 1

Introduction

The goal for this thesis is to develop and implement an autonomous landing mode for the quadrotor developed by the AIICS team at Linköping University, the LinkQuad.

The size of the system poses limitations on the payload and processing power available in-flight. This means that the implementations has to be done in an efficient manner on the small computers that are available on the LinkQuad.

The limitations, however, do not stop us from utilizing advanced estimation and control techniques, and it turns out that the LinkQuad design is in fact very suitable for the camera-based pose estimation. This estimation can be efficiently detached from the core control and modularized as an independent sensor, which will be exploited in the thesis.

1.1 Unmanned Aerial Vehicles

As noted in [11], Unmanned Aerial Vehicles (UAV's) have been imagined and constructed for millennia, starting in ancient Greece and China. The modern concept of UAV's was introduced in the first world war, which illuminates the dominant role that the military has played in the field over the last century. A commonly cited alliteration is that UAV's are intended to replace human presence in missions that are "Dull, Dirty and Dangerous".

While the military[8] continue to lead the development in the field, recent years have seen a great increase in domestic and civilian applications[14]. These applications range from pesticide dispersing and crop monitoring to traffic control, border watch and rescue scenarios[2].

The type of UAV that is used in the implementation of this thesis falls under the category of Small Unmanned Aerial Vehicles (SUAV's). SUAV's are designed to be man-portable in weight and size and is thus limited in payload and availabe processing power. This limitation, in combination with the unavailability of indoor GPS positioning, has led to extensive use of off-board positioning and control in recent research. Systems developed by for instance Vicon[1] and Qualisys[2] yield positioning with remarkable precision, but they also limit the application to a confined environment with an expensive setup.

This thesis seeks a different approach, with an efficient self-contained on-board implementation. GPS and external cameras are replaced by inertial sensors and an on-board camera which uses visual SLAM to position the LinkQuad relative to its surroundings.

1.2 The Platform

The LinkQuad is a modular quadrotor developed at Linköping University. The core configuration is equipped with standard MEMS sensors (accelerometers, gyroscopes and a magnetometer), but for our purposes we have also mounted a monocular camera which feeds data into a microcomputer specifically devoted to the processing of the camera feed. This devoted microcomputer is what allows the primary on-board microcomputer to focus on state estimation and control, without beeing overloaded by video processing.

The primary microcomputer is running a framework named C++ Robot Automation Platform (CRAP), which was developed by the thesis' author for this purpose. CRAP is a light-weight automation platform with a purpose similar to that of ROS[3]. It is, in contrast to ROS, primarily designed to run on the kind relatively low-end Linux systems that fits the payload and power demands of a SUAV. The framework is further described in Appendix **??**.

Using the framework, the functionality of the implementation is distributed in separate modules.

Observer Sensor fusing state estimation. Chapter 2.

Control Outer loop LQ control. Chapter 3.

Logic State-machine for scheduling controller model and reference trajectory. Chapter 4.

1.3 Previous Work

The problem of positioning an unmanned quadrotor using visual feedback is a problem which was only fairly recently solved [1, 13]. Few have attempted to use on-board sensors only

1.4 Objectives

The main objective for the thesis is to perform autonomous landing with the LinkQuad. To achieve this,

[1] `http://www.vicon.com/`
[2] `http://www.qualisys.com/`
[3] `http://www.ros.org/`

1.5 Contributions

None

1.6 Thesis Outline

Chapter 2

State Estimation

A central part of automatic control is to know the state of the device you are controlling. The system studied in this thesis - the LinkQuad - is in constant motion, so determining the up-to-date position if of vital importance to the performance of the control. This chapter deals with the estimation of the states relevant for positioning and controlling the LinkQuad. Filter theory and notation is established in Section 2.1.

In this thesis, an Unscented Kalman Filter (UKF) is used, which extends the linear Kalman filter theory to a non-linear model in an appealing black-box way. The theory of the UKF is treated in Section 2.2.

The motion model of the system is derived and discussed in Section **??**.

The motions of the system is also captured by the on-board sensors. A measurement z is related to the motion model by the sensor model h;

$$z(t) = h(x(t), u(t), t) \tag{2.1}$$

The models for the sensors used on the LinkQuad are discussed in Section **??**.

2.1 The Filtering Problem

The problem of estimating the state of a system - in this case it's position, orientation, velocity etc. - is in the Kalman filter framework expressed as the problem of finding the state estimate $\hat{x}$ that in a well defined best way (e.g. with Minimum Mean Square Error, MMSE) describes the behaviour of the system.

The evolution of a system plant is traditionally described by a set of differential equations that link the change in the variables to the current state and known inputs, u. The system is also assumed to be subject to an additive white Gaussian noise $v(t)$ with known covariance Q. This introduces an uncertainty associated with the system, which accounts for imperfections in the model compared to the physical real-worl-system.

$$\dot{x}(t) = f_c(x(t), u(t), t) + v_c(t) \tag{2.2}$$

With numeric or analytical solutions, we can obtain the discrete form of (2.2), where only the sampling times are considered. The control signal, $u(t)$, is for instance assumed to be constant in the time interval, and we obtain obtain the next predicted state directly, yielding the prediction of $\hat{x}$ at the time t *given* the information at time $t-1$. [1] This motivates the notation used in this thesis - $\hat{x}_{t|t-1}$.

$$x_{t|t-1} = f(x_{t-1|t-1}, u_t, t) + v(t) \tag{2.3}$$

In the ideal case, a simulation of a prediction $\hat{x}$ would with the prediction model in (2.3) fully describe the evolution of the system. To be able to provide a good estimate in the realistic case, however, we must also feed back measurements given from sensors measuring properties of the system.

These measurements, z_t, are fed back and fused with the prediction using the *innovation*, ν.

$$\nu_t = z_t - \hat{z}_t \tag{2.4}$$

That is, the difference between the measured value and what would be expected in the ideal (simulated) case. To account for disturbances affecting the sensors, the measurements are associated with an additive white Gaussian noise $w(t)$, with known covariance R.

$$\hat{z}_t = h(\hat{x}_t, u_t, t) + w(t) \tag{2.5}$$

The innovation is then fused with the prediction to yield a new estimation [3] of x given the information available as of the time t.

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t \nu_t \tag{2.6}$$

The choice of K_t is a balancing between of trusting the model, or trusting the measurement. In the Kalman filter framework, this balancing is made by tracking and weighing the uncertainties introduced by the prediction and the measurement noise.

Because of the assumptions on the noise and the linear property of the innovation feedback, the Gaussian property of the noise is preserved in the filtering process. The system states can thus ideally be considered drawn from a normal distribution.

$$x \sim \mathcal{N}(\hat{x}, P_{xx}) \tag{2.7}$$

Conditioned on the state and measurements before time k, the covariance of the sample distribution is defined as

$$P_{xx}(t|k) = E\left[\left\{x(t) - \hat{x}_{t|k}\right\}\left\{x(t) - \hat{x}_{t|k}\right\}^T |\mathcal{Z}^j\right]. \tag{2.8}$$

As new measurements are taken, the covariance of the state evolves [5] with the state estimate as

$$P_{xx}(t|t) = P_{xx}(t|t-1) - K_t P_{\nu\nu}(t|t-1) K_t^T \tag{2.9}$$

[1] Note that we have not yet performed any measurements that provide information about the state at time t.

$$P_{\nu\nu}(t|t-1) = P_{zz}(t|t-1) + R(t). \tag{2.10}$$

K is derived in e.g. [3] as

$$K_t = P_{xz}(t|t-1)P_{\nu\nu}^{-1}(t|t-1), \tag{2.11}$$

given the cross-correlation of the predicted state and output, P_{xz}.

There are several approaches to how to propagate the covariance through the prediction-model to acquire $P_{xx}(t|t-1)$ with retained Gaussian properties. As the linear case is simple;

$$P_{xx}(t|t-1) = AP(t|t)A^T + Q_t; \tag{2.12}$$

a novel approach is to linearize the system for A. This linearization, however, fails to capture the finer details of highly non-linear systems and may furthermore be tedious to calculate, analytically or otherwise. A different approach is discussed in Section 2.2.

2.2 The Unscented Kalman Filter

The basic version of the Unscented Kalman Filter was proposed in [5] based on the following intuition [5]

> *With a fixed number of parameters it should be easier to approximate a Gaussian distribution than it is to approximate an arbitrary nonlinear function.*

The approach is thus to propagate the uncertainty of the system through the non-linear system and fit the results as a Gaussian distribution. The propagation is made by simulating the system in the prediction model for carefully chosen offsets from the current state called *sigma points*, each associated with a weight of importance. The selection scheme for these points can vary (and yield other types of filters), but a common choice is the *Scaled Unscented Transform* (SUT) [12]. The SUT uses a minimal set of sigma points needed to describe the first two moments of the propagated distribution - two for each dimension (n) of the state vector and one for the mean.

$$\begin{aligned}
\mathcal{X}_\mathbf{0} &= \hat{x} \\
\mathcal{X}_\mathbf{i} &= \hat{x} + \left(\sqrt{(n+\lambda)P_{xx}}\right)_i \qquad && i = 1, \cdots, n \\
\mathcal{X}_\mathbf{i} &= \hat{x} - \left(\sqrt{(n+\lambda)P_{xx}}\right)_i \qquad && i = n+1, \cdots, 2n
\end{aligned} \tag{2.13}$$

$$\begin{aligned}
W_0^m = \tfrac{\lambda}{n+\lambda} \quad W_0^c &= \tfrac{\lambda}{n+\lambda} + (1-\alpha^2+\beta) \\
W_i^m = W_i^c &= \tfrac{1}{2(n+\lambda)} \qquad i = 1, \cdots, 2n
\end{aligned} \tag{2.14}$$

$$\lambda = \alpha^2(n+\kappa) - n \tag{2.15}$$

Variable	**Value**	**Description**
α	$0 \leq \alpha \leq 1$ (e.g. 0.01)	Scales the size of the sigma point distribution. A small α can be used to avoid large non-local non-linearities.
β	2	As discussed in [4], β affects the weighting of the center point, which will directly influence the magnitude of errors introduced by the fourth and higher order moments. In the strictly Gaussian case, $\beta = 2$ can be shown to be optimal.
κ	0	κ is the number of times that the centerpoint is included in the set of sigma points, which will add weight to the centerpoint and scale the distribution of sigma points.

Table 2.1. Description of the parameters used in the SUT.

The three parameters introduced here, α, β and κ are summarized in table 2.2. The term $\left(\sqrt{(n+\lambda)P_{xx}}\right)_i$ is used to denote the i'th column of the matrix square root $\sqrt{(n+\lambda)P_{xx}}$.

When the sigma points $\mathcal{X}_\mathbf{i}$ has been calculated, they are propagated through the non-linear prediction function and the resulting mean and covariance can be calculated.

$$\mathcal{X}_\mathbf{i}^{+\mathbf{1}} = f(\mathcal{X}_\mathbf{i}, u, t) \qquad i = 0, \cdots, 2n \tag{2.16}$$

$$\hat{x} = \sum_{i=0}^{2n} W_i^m \mathcal{X}_\mathbf{i}^{+\mathbf{1}} \tag{2.17}$$

$$P_{xx} = \sum_{i=0}^{2n} W_i^c \left\{\mathcal{X}_\mathbf{i}^{+\mathbf{1}} - \hat{z}\right\} \left\{\mathcal{X}_\mathbf{i}^{+\mathbf{1}} - \hat{z}\right\}^T \tag{2.18}$$

For the measurement update, similar results are obtained, and the equations (2.21)-(2.22) can be connected to equations (2.10)-(2.11).

$$\mathcal{Z}_\mathbf{i} = h(\mathcal{X}_\mathbf{i}, u, t) \qquad i = 0, \cdots, 2n \tag{2.19}$$

$$\hat{z} = \sum_{i=0}^{2n} W_i^m \mathcal{Z}_\mathbf{i} \tag{2.20}$$

$$P_{zz} = \sum_{i=0}^{2n} W_i^c \left\{\mathcal{Z}_\mathbf{i}^\mathbf{x} - \hat{z}\right\} \left\{\mathcal{Z}_\mathbf{i} - \hat{z}\right\}^T \tag{2.21}$$

$$P_{xz} = \sum_{i=0}^{2n} W_i^c \left\{\mathcal{X}_\mathbf{i} - \hat{x}\right\} \left\{\mathcal{Z}_\mathbf{i} - \hat{z}\right\}^T \tag{2.22}$$

As can be seen from the equations in this section, the UKF handles the propagation of the probability densities through the model without the need for explicit calculation of the Jacobians of Hessians for the system. The filtering is based solely on function evaluations of small offsets from the expected mean state, be it for the measurement functions, discussed in Section **??**, or the time update prediction function - the motion model.

Chapter 3

Controller

To control the quadrotor's movements, a controller is applied to the physical system, using a model of the system to calculate the best (in a sense well defined in this chapter) signals of control to each of the engines driving the propellers.

The approach chosen in this thesis is based on the Linear Quadratic (LQ) controller, the theory of which is presented in Section **??**. The physical model of the system was

Chapter 4

Logic

Chapter 5

Video

Chapter 6

Conclusions

6.1 Further work

Wind model, drag model, wind momentum on body

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