Project Ideas for the Course Dynamic Vision

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This document lists some project *ideas* that can be carried out within the graduate course *Dynamic Vision*. It will be updated as time goes by, my aim is to provide at least one slightly more detailed project idea per lecture. Note that all of the projects below have to be specialized in order to be manageable, otherwise they can easily become very large. Hence, as always, it is very important to break down the problem in suitable and manageable pieces.

1 Camera Calibration Using Gray-Box System Identification

Standard camera calibration algorithms and available software, see, e.g., Bouguet (2008), makes use of a couple of images acquired from different poses. The idea here is to use a movie as input. The parameter vector θ should contain the intrinsic camera parameters and the lens distortion parameters (not the camera poses!). The camera pose will be obtained by solving an appropriate estimation problem instead.

One way of solving this problem is by using the flexible gray-box framework Ljung (1999); Graebe (1990), where the resulting optimization problem is formulated using the prediction error method. The goal of this method is to find the parameters θ that minimizes the prediction error

$$\varepsilon_t(\theta) = y_t - \hat{y}_{t|t-1}(\theta), \tag{1}$$

i.e., the distance between the one-step ahead prediction from the model $\hat{y}_{t|t-1}(\theta)$ and the observed measurement y_t. The predictor is obtained by using a dynamic model (describing the motion of the camera) and a camera models. Useful inspiration can probably be found in Hol et al. (2008). Hence, the identification problem to be solved is

$$\hat{\theta} = \arg\min_{\theta} V(\theta), \tag{2}$$

where

$$V(\theta) = \frac{1}{N}\sum_{t=1}^{N} \frac{1}{2}\varepsilon_t^T(\theta)\Lambda_t^{-1}\varepsilon_t(\theta), \tag{3}$$

where Λ_t is a suitably chosen weighting matrix.

As always is the case with gray-box identification, it is important to have a good initial guess, which can be obtained similarly to what was done in Zhang (2000).

2 Autonomous Landing of a UAV in an Unknown Area

In the course literature (Ma et al., 2006) the authors briefly describe a pose estimator aimed at providing information for autonomous landing of an Unmanned Aerial Vehicle (UAV). A similar system was recently derived and implemented in one of our recent Master's theses Salomonsson and Saläng (2008). The limitation in the aforementioned approaches is that they both assume that the helicopter is landing at a predefined position, where an artificial landing pad is placed in advance.

The aim of this project is to design and implement an estimator for autonomous UAV landing, when there is no landing pad available. This implies that the estimator must, besides the UAV state, deliver a map of the terrain under the UAV. In order words it is a SLAM problem that has to be solved. This map should then be used to judge where it is safe to land, which roughly corresponds to deciding if the ground plane is "sufficiently horizontal".

As far as I know the first autonomous landing of an unmanned helicopter in an unknown area was achieved by NASA in 2004 and the system is described in Johnson et al. (2005). At least one additional sensor besides the camera has to be used in order to obtain the overall scale of the scene. For this project it is recommended that the combined camera IMU sensor unit illustrated in Figure 1 is used. An interesting alternative sensor combination that could be

Figure 1: *The sensor unit, consisting of an IMU and a camera.*

investigated is to make use of a camera and an ultrasonic sensor. In order to test and validate the performance of the estimator our industrial robot can be used. Furthermore, depending on the progress, we have UAV's that can be used to test the solution.

3 Bicycle Identification and Pose Estimation

The task in this project is to investigate the possibility of making use of a quite detailed dynamic model of a bicycle together with measurements from an inertial measurement unit (IMU) and a camera in order to estimate the bicycle state. The combined camera and IMU sensor unit illustrated in Figure 1 can be used for field tests. In Figure 2 we provide the basic geometry of a bicycle, borrowed from Åström and Murray (2008). The task of deriving an accurate

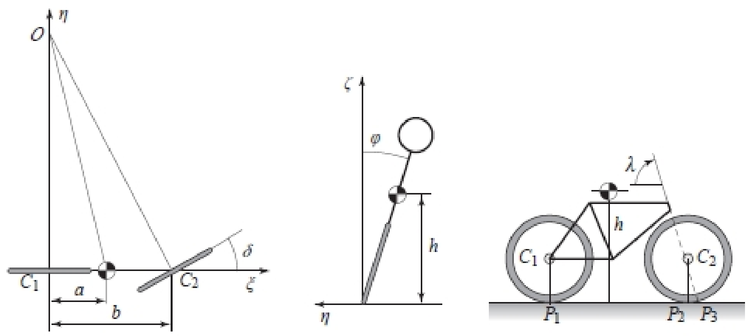

Figure 2: *Schematic views of a bicycle, borrowed from Åström and Murray (2008). The steering angle is δ, and the roll angle is ϕ.*

dynamic model of a bicycle can be very complex. However, as always much can be achieved in using rather simple models. The so called Whipple model provides a reasonable compromise. This model is given by

$$M\begin{pmatrix}\ddot{\varphi}\\ \ddot{\delta}\end{pmatrix} + Cv_0\begin{pmatrix}\dot{\varphi}\\ \dot{\delta}\end{pmatrix} + (K_0 + K_2v_0^2)\begin{pmatrix}\varphi\\ \delta\end{pmatrix} = \begin{pmatrix}0\\ T\end{pmatrix} \tag{4}$$

where v_0 denote the forward velocity of the bicycle. Furthermore, M, C, K_0, K_2 are 2×2 matrices depending on the geometry and mass distribution of the bicycle. For a good control oriented introduction and overview of the bicycle dynamics we refer to Åström et al. (2005); Åström and Murray (2008).

The project can be split into two sub-projects or possibly two different projects.

- *Modelling and system identification:* Derive a model for the bicycle position, orientation and velocity that can be used together with the camera and IMU sensor unit. This also includes system identification, since the bicycle dynamics contains quite a few parameters.

- *State estimation and possibly SLAM:* Estimate the states (position, orientation, velocity, etc.) of the bicycle based on the measurements from the camera IMU sensor unit. This obviously requires a model. If the first sub-project has been solved the model derived in that project can be used. However, if the first sub-project has not been solved a simpler nominal model can be used, see e.g., `www.cds.caltech.edu/~murray/amwiki/index.php?title=Bicycle_dynamics` for reasonable values for a standard bicycle. The problem can either be cast as a visual odometry problem or perhaps more interesting as a SLAM problem.

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