Single-camera SLAM using the SceneLib library

Paul Smith

Robotics Research Group Talk, Nov 2005
1. Introduction
   - The Camera as a Position Sensor
   - Visual SLAM

2. Davison’s MonoSLAM
   - Overview and Nomenclature
   - Extended Kalman Filter
   - Automatic Map Management
   - Performance

3. The SceneLib Libraries
   - Introduction
   - The Scene Library
   - The MonoSLAM Library
   - Applications using SceneLib

4. Final Thoughts
   - Final Thoughts
The Camera as a Position Sensor

**Aim**
- Use a camera as a position sensor

**Challenges**
- Monocular (no depth)
- Unconstrained
- High acceleration & large rotations
- Usually want real-time localisation
Off-line Processing

Structure from motion

- Typical Computer vision approach
- Bundle adjustment over a long sequence
- Applied to post-production, 3D model reconstruction.
Sequential Real-time Processing

Simultaneous Localisation and Mapping (SLAM)

- Typical robotics approach.
- Building a long-term map by propagating and correcting uncertainty.
- Mostly used in simplified 2D environments with specialised sensors such as laser range-finders.
Classic Approaches to Visual SLAM

Davison, ICCV 2003
- Traditional SLAM approach (Extended Kalman Filter)
- Maintains full camera and feature covariance
- Limited to Gaussian uncertainty only

Nistér, ICCV 2003
- Structure-from-motion approach (Preemptive RANSAC)
- Frame-to-frame motion only
- Drift: No repeatable localisation
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Recent Approaches to Visual SLAM

Pupilli & Calway, BMVC 2005
- Traditional SLAM approach (Particle Filter)
- Greater robustness: handles multi-modal cases
- New features not rigorously initialised

Eade & Drummond, 2006
- FastSLAM approach (Particle Filter/Kalman Filter)
- Particle per camera hypothesis, Kalman filter for features
- Allows larger maps: update $O(M \log N)$ instead of $O(N^2)$
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Davison’s MonoSLAM: Overview

Main features

- Initialisation with known target
- Extended Kalman Filter
  - ’Constant velocity’ motion model
  - Image patch features with Active Search
- Automatic Map Measurement
- Particle filter for initialisation of new features
The camera

- The **camera position state** $x_p$ is its 3D position and orientation

$$x_p = \begin{pmatrix} r^W \\ q^{WR} \end{pmatrix} = \begin{pmatrix} x \\ y \\ z \\ q_0 \\ q_x \\ q_y \\ q_z \end{pmatrix}$$

- The **camera state** $x_v$ contains $x_p$ plus optional additional state information (e.g. velocity and angular velocity)
Nomenclature

Features

- Each feature $y_i$ is a 3D position vector

$$y_i = \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix}$$
PDF over camera and feature state is modelled as a single multi-variate Gaussian and we can use the Extended Kalman Filter.
Extended Kalman Filter: Prediction Step

**Time Update**

1. Estimate new location
2. Add process noise
Extended Kalman Filter: Prediction Step

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Extended Kalman Filter: Prediction Step

1. Project the state ahead

\[ \hat{x}_{\text{new}} = f(\hat{x}, u) \]

2. Project the error covariance ahead

\[ P_{\text{new}} = \frac{\partial f}{\partial x} P \frac{\partial f}{\partial x}^T + Q \]
Extended Kalman Filter: Motion models

Constant velocity

Assume bounded, Gaussian-distributed linear and angular acceleration

\[
\mathbf{x}_{\text{new}} = \begin{pmatrix}
\mathbf{r}^{W}_{\text{new}} \\
\mathbf{q}^{WR}_{\text{new}} \\
\mathbf{v}^{W}_{\text{new}} \\
\mathbf{\omega}^{R}_{\text{new}} \\
\end{pmatrix} = f(\mathbf{x}, \mathbf{u}) = \begin{pmatrix}
\mathbf{r}^{W} + (\mathbf{v}^{W} + \mathbf{V}^{W}) \Delta t \\
\mathbf{q}^{WR} \times \mathbf{q} ((\mathbf{\omega}^{R} + \Omega^{R}) \Delta t) \\
\mathbf{v}^{W} + \mathbf{V}^{W} \\
\mathbf{\omega}^{R} + \Omega^{R} \\
\end{pmatrix}
\]
Extended Kalman Filter: Update Step

Measurement Update

1. Measure feature(s)
2. Update positions and uncertainties
Extended Kalman Filter: Update Step

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**Extended Kalman Filter: Update Step**

**Measurement Update**

1. Make measurement $z$ to give the innovation $\nu$
   \[
   \nu = z - h(\hat{x})
   \]

2. Calculate innovation covariance $S$ and Kalman gain $W$
   \[
   S = \frac{\partial h}{\partial x} P \frac{\partial h}{\partial x}^T + R
   \]
   \[
   W = P \frac{\partial h}{\partial x} S^{-1}
   \]

3. Update estimate and error covariance
   \[
   \hat{x}_{\text{new}} = \hat{x} + W \nu
   \]
   \[
   P_{\text{new}} = P - W S W^T
   \]
Measurement Step: Image Features and the Map

- Feature measurements are the locations of salient image patches.
- Patches are detected once to serve as long-term visual landmarks.
- Sparse set of landmarks gradually accumulated and stored indefinitely.
Measurement Step: Active Search

- **Active search** within elliptical search regions defined by the feature innovation covariance.
- Template matching via **exhaustive correlation search**.
Automatic Map Management

- Initialise system from a few known features.
- Add a new feature if number of visible features drops below a threshold (e.g. 12).
- Choose salient image patch from a search box in an underpopulated part of the image.
Monocular Feature Initialisation with Depth Particles

A new feature has unknown depth

1. Populate the line with 100 particles, spaced uniformly between 0.5m and 5m from the camera.
2. Match each particle in successive frames to find probability of that depth.
3. When depth covariance is small,
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2. Match each particle in successive frames to find probability of that depth.
3. When depth covariance is small, convert to Gaussian.
Feature initialisation

- New features need adding to the state vector and covariance matrix.

Increasing the state size dynamically

\[ x_{\text{new}} = \begin{pmatrix} x_v \\ y_1 \\ y_2 \\ y_i \end{pmatrix}, \quad P = \begin{bmatrix} P_{xx} & P_{xy_1} & P_{xy_2} \\ P_{y_1x} & P_{y_1y_1} & P_{y_1y_2} \\ P_{y_2x} & P_{y_2y_1} & P_{y_2y_2} \\ \frac{\partial y_i}{\partial x_v} & \frac{\partial y_i}{\partial x_v} & \frac{\partial y_i}{\partial x_v} & \frac{\partial y_i}{\partial h_G} & \frac{\partial y_i}{\partial h_G} \end{bmatrix} \]
Feature deletion

- Delete a feature if more than half of attempted measurements fail.

Reducing the state size dynamically

\[
\begin{bmatrix}
    P_{xx} & P_{xy_1} & P_{xy_2} & P_{xy_3} \\
    P_{y_1x} & P_{y_1y_1} & P_{y_1y_2} & P_{y_1y_3} \\
    P_{y_2x} & P_{y_2y_1} & P_{y_2y_2} & P_{y_2y_3} \\
    P_{y_3x} & P_{y_3y_1} & P_{y_3y_2} & P_{y_3y_3}
\end{bmatrix}
\rightarrow
\begin{bmatrix}
    P_{xx} & P_{xy_1} & P_{xy_3} \\
    P_{y_1x} & P_{y_1y_1} & P_{y_1y_3} \\
    P_{y_2x} & P_{y_2y_1} & P_{y_2y_3} \\
    P_{y_3x} & P_{y_3y_1} & P_{y_3y_3}
\end{bmatrix}
\]
Example Sequence
What Enables It To Run In Real-time?

Timings

<table>
<thead>
<tr>
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<th>Time</th>
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</tr>
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Easily manages 30Hz processing on a 3.4GHz desktop PC using C++, Linux, OpenGL

Main time-saving features

- Automatic map management criteria to maintain a sufficient but sparse map
- Active search guided by uncertainty
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The SceneLib Libraries

- A complete basic Davison MonoSLAM system
- Written in standard C++
- Three libraries and an application
  - **SceneLib**: A generic SLAM library. Base classes for motion models, features, measurements and the Kalman Filter.
  - **SceneImproc**: Image processing for MonoSLAM (i.e. feature detection and correlation)
  - **MonoSLAM**: Specific motion and feature-measurement models for single-camera SLAM, and a control class.
  - **MonoSLAMGlow**: Application based on GLOW/GLUT library which uses the libraries.
Obtaining the SceneLib libraries

- All files available from the Active Vision CVS repository
- Will also need VW34 library (soon to be VW35)

**Getting and building files from CVS**

```bash
cvs -d/data/lav-local/common/cvsroot co VW34
cvs -d/data/lav-local/common/cvsroot co SceneLib
cvs -d/data/lav-local/common/cvsroot co MonoSLAMGlow
cd VW34
./bootstrap
./configure
make
cd ../SceneLib
./configure
make
cd ../MonoSLAMGlow
make
```
Running the MonoSLAMGlow application

Running MonoSLAMGlow

./scenerob

- Comment out `-D_REALTIME_` in Makefile to use previously saved image sequence
Making and viewing documentation

```
cd SceneLib
make docs
firefox html/index.html
```
The Scene library

- **Scene** is a generic SLAM library.

### Main Scene classes

- **Scene_Single** Stores the full system state and manages features.

- **Feature** Stores and manages a feature’s state vector and covariances

- **Motion_Model** Base class for all motion models.

- **Feature_Measurement_Model** Base class for all feature and measurement models.

- **Sim_Or_Rob** Base class for something that can make measurements.

- **Kalman** Friend class of **Scene_Single** that implements a Kalman filter.
The Scene library

- The main Scene classes are completely generic:
  - **Scene_Single** stores the 'robot' state vector \( \mathbf{x}_v \), covariance \( \mathbf{P}_{xx} \) and a list of Features.
  - **Feature** stores a feature state vector \( \mathbf{y}_i \), its covariances \( \mathbf{P}_{xv}, \mathbf{P}_{y_i}, \mathbf{P}_{y_jy_i} \) and \( \mathbf{P}_{y_iy_j} (\forall j < i) \).
  - **Kalman** updates the state given measurements via **Sim_Or_Rob**.
- The **Motion_Model** and **Feature_Measurement_Model** classes access and interpret the state.
- Classes in MonoSLAM derived from these base classes make the application specific.
Motion model classes

- A **Motion_Model** knows how to perform the state update
  \[ \hat{x}_{vnew} = f_v(\hat{x}_v, u) \]
- It stores no state itself

**Main functions**

- **func_fv_and_dfv_by_dxv(xv,u,delta_t)** Calculates the new camera state \( \hat{x}_{vnew} \) and Jacobian \( \frac{\partial f_v}{\partial x_v} \)
- **func_Qi(xv,u,delta_t)** Calculates the covariance \( Q_i \) of the process noise.
A `Feature_Measurement_Model` knows how to manage a feature’s state and predict a measurement $h_i = h(y_i, x_p)$.

- It stores no state itself.
- Subclassed into two special types:
  - `Fully_Init_Wide_Point_Feature_Measurement_Model` A complete feature in the SLAM map.
  - `Partially_Init_Wide_Point_Feature_Measurement_Model` A feature currently being initialised.
**Fully-initialised Features**

- A `Fully_Initiated_Feature_Measurement_Model` understands the state of a full feature and determines how it is measured.
- It stores no state itself.

**Main functions**

- `func_hi_and_dhi_by_dxp_and_dhi_by_dyi(yi, xp)` Calculates the expected measurement vector $h_i$ and its Jacobians $\frac{\partial h_i}{\partial x_p}$ and $\frac{\partial h_i}{\partial y_i}$.
- `func_Ri(hi)` Calculates the measurement noise $R_i$.
- `visibility_test(xp, yi, xp_orig, hi)` Decides whether a feature should be measured.
- `func_Si(Pxx, Pxyi, Pyiyi, dhi_by_dxv, dhi_by_dyi, Ri)` Calculates the innovation covariance $S_i$. 
A *Partially_Initiated_Feature_Measurement_Model* handles a feature which still has some free parameters $\lambda$.

Each partially-initialised feature references a *FeatureInitInfo*

*FeatureInitInfo* stores a vector of *Particles* representing possible $\lambda$s and their probabilities.

A *Partially_Initiated_Feature_Measurement_Model* can convert its feature into a fully-initialised feature.
Partially-initialised Features

**Main functions**

*func_hpi_and_dhpi_by_dxp_and_dhpi_by_dyi(yi, xp, lambda)*
Calculates the expected measurement vector \(h_i\) and its Jacobians, given values of the free parameters \(\lambda\).

*func_Ri(hi)*
Calculates the measurement noise \(R_i\).

*visibility_test(xp, yi, xp_orig, hi)*
Decides whether a feature should be measured.

*func_Si(Pxx, Pxyi, Pyiyi, dhi_by_dxv, dhi_by_dyi, Ri)*
Calculates the innovation covariance \(S_i\).

*func_yfi_and_dyfi_by_dypi_and_dyfi_by_dlambda(ypi, lambda)*
Converts a partially-initialised into a fully-initialised feature.
The MonoSLAM library provides:

- Specialisations of Scene base classes:
  - `Impulse_ThreeD_Motion_Model` and `ZeroOrder_ThreeD_Motion_Model` motion models.
  - `Fully_Init_Wide_Point_Feature_Measurement_Model` and `Line_Init_Wide_Point_Feature_Measurement_Model`.
  - `Robot` (derived from `Sim_Or_Rob`) to handle image feature measurement.

- A `MonoSLAM` class to provide the main interface.
- Functions to draw the two graphical displays.
The MonoSLAM Class

- **The MonoSLAM** class provides the basic SLAM functionality

**Main functions**

- **GoOneStep(image, delta_t, currently_mapping_flag)** Step the system onto the next frame. (*image* is ignored, and instead it must be set using *Scene_Single::load_new_image()*).

- The **MonoSLAMInterface** class provides full control and feedback functions.

**Main functions**

- **GetScene()** Get the *Scene_Single* class.
- **GetRobot()** Get the *Robot* class.

plus >40 other *Get() and Set()* functions.
The MonoSLAMGlow Application

Failed match
Successful match
Unused feature
Other MonSLAM Applications
Live Demonstration
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Final Thoughts: EKF-based Visual SLAM

Observations
- The Davison visual SLAM system works!
- It works reliably enough for a live demo.
- It needs no real hidden tricks needed to make it work.

Discussion
- Need more, better features to track
  - Faster initialisation (fewer particles?)
  - Use full-frame fast feature detection
- Better initialisation: how do we deal with points at infinity?
- Motion model: How do we get smoother, better tracks?
- Loop closing
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- The SceneLib libraries are (reasonably) well-designed and (reasonably) well-documented
- They make it easy to write a Davison-style visual SLAM application

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- Are they useful to the Active Vision group?
- Can we all use them and get the benefits in code sharing that that will bring?
- Can we at least all use the same nomenclature and colours?
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