SLAM for an AUV using vision and an acoustic beacon

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Cooperative Navigation and Control of Multiple Robotic Vehicles
Theory and Practice
EECI, Supélec
February 21-25, 2011
Introduction

Motivation

- Applications with ocean robotics have increased dramatically. There are a vast demand for advance navigation and positioning systems for autonomous/remotely operated underwater vehicles
- Challenging problem: Electromagnetic signals do not propagate well below the sea surface
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Approaches

- Acoustic beacon navigation (USBL, LBL, GIB)
- Terrain based navigation
- Vision based SLAM
Body-fixed \( \{B\} \), camera-fixed \( \{C\} \), earth-fixed (inertial) \( \{I\} \), and visual-fixed \( \{V\} \) coordinate frames used in problem

- \( ^B_A R \): Rotation matrix form \( \{A\} \) to \( \{B\} \)
- \( ^B_Q \): Position of the vector \( Q \) expressed in \( \{B\} \)
- \( ^B_P A \): Position of the origin of frame \( \{A\} \) expressed in \( \{B\} \)
Equations of motion

**Kinematics**

\[
\begin{bmatrix}
\dot{\eta}_1 \\
\dot{\eta}_2
\end{bmatrix} =
\begin{bmatrix}
J_1(\eta_2) & 0_{3\times3} \\
0_{3\times3} & J_2(\eta_2)
\end{bmatrix}
\begin{bmatrix}
\nu_1 \\
\nu_2
\end{bmatrix} \Leftrightarrow \dot{\eta} = J(\eta_2)\nu
\]

\(\eta_1\) – linear position; \(\eta_2\) – attitude; \(\nu_1\) body-fixed linear velocities; \(\nu_2\) – body-fixed angular velocities.
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**Dynamics**

\[M_{RB} \ddot{\nu} + C_{RB}(\nu)\nu = \tau_{RB}\]

\(M_{RB}, C_{RB}(\nu)\) denote the rigid body inertia matrix and the matrix of Coriolis and Centrifugal terms, and \(\tau_{RB}\) represents the total forces and moments applied on body.

\[\tau_{RB} = \tau + \tau_A + \tau_D + \tau_R + \tau_d\]

\(\tau_R\) – buoyancy and gravity; \(\tau_A\) – added mass term; \(\tau_D\) – damping and lift effects; \(\tau\) – thrusters forces and moments; \(\tau_d\) – input disturbances.
Sensor measurements

Inertial measurement unit (IMU)

Provides measurements of angular velocities $\nu_2 = [p, q, r]^T$ and attitude $\eta_2 = [\phi, \theta, \psi]^T$ with respect to earth-fixed (inertial) $\{I\}$. 

Pressure sensor

Measures the depth $z$.

Acoustic beacon

Range measurements from the position of the vehicle to a single fixed buoy with known position $\|\eta_1 - Q_b\|^2$. 

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$$\|\eta_1 - Q_b\|_2$$
Monocular charged-coupled-device (CCD) camera

For feature $i$, the corresponding output can be written as

$$y_{ccd}^i = \frac{1}{\mu_i} F^c Q_i + v_i$$

with the constraint

$$[0, 0, 1] y_{ccd}^i = 1$$

After some transformations the output equation using $\mathcal{T}Q_i$ can be written

$$y_{ccd}^i = \frac{1}{\mu_i} [F^c P_B + F^c R \mathcal{T} R' (\mathcal{T}Q_i - \mathcal{T} P_B)] + v_i$$
EKF-SLAM algorithm can be decomposed in three steps:

1. Predict the state estimate using the process model and the input signal $u$. 
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2. Update the current state estimate using the measurements including the re-observed features.
EKF-SLAM

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1. Predict the state estimate using the process model and the input signal $u$.

2. Update the current state estimate using the measurements including the re-observed features.

3. Augment the state of the filter if there are new features.
Motivation

The motivation arises from the fact that the EKF-SLAM convergence is very sensitive to the initial guess of $\mu_i$. The initial guess of the $\mu_i$ should be close enough to the real value, for the algorithm to converge.
Multiple model EKF-SLAM

Approach

- From a range measurement sensor (or a priori estimate of the image depth) generate as many multiple models as needed.
- Apply a multiple model adaptive estimation scheme.
- Augment the best converged model into SLAM.

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Basic Idea of the MMAE Method
• Construct a bank of $N$ discrete-time Kalman filters, each KF "matched" to each of the $N$ possible models
• Each KF generates (in real-time) a local state-estimate vector and a residual vector
• All of the $N$ available KF residual vectors are used to compute (on-line) the posterior probability $P_k(t)$, $k=1,2, \ldots, N$, that the $k$th model is indeed the true one (I.e. the one that generates the data)
• The overall MMAE state-estimate is formed by weighting the $N$ local state-estimates by the corresponding posterior probability
• The overall MMAE state-covariance matrix is formed by weighting the local state-covariance matrices by the corresponding posterior probability, including a correction that involves the global conditional mean

The MMAE Filter

\[
\begin{align*}
&u(t-1) \\
&z(t) \\
&EKF 1 \\
&EKF 2 \\
&\ldots \\
&EKF N \\
&S_1(t) \\
&S_2(t) \\
&S_N(t) \\
&\text{Posterior Probability Evaluator} \\
&\text{Residual covariances} \\
&P_1(t) \\
&P_2(t) \\
&P_N(t) \\
&\hat{x}(t/t) \\
&\Pi \\
&\Pi \\
&\Pi \\
&\Sigma
\end{align*}
\]
Simulations

Multiple model EKF-SLAM

Multiple model EKF-SLAM without acoustic beacon

EKF-SLAM

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**Simulations**

Multiple model

**EKF-SLAM**

**Multiple model EKF-SLAM without acoustic beacon**

**EKF-SLAM**
Conclusions

- The key contribution was the use of multiple model adaptive estimation tools to extend the standard EKF-SLAM.

- The simulation results illustrated the efficiency of this new approach.

- The computation power needed to use the multiple model EKF-SLAM is in the same order of the standard EKF-SLAM after the convergence of the multiple models.