Title

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Chapter 1

Introduction

1.1 Literature Review

1.1.1 infinite-dimensional observers

linear:
-observer theory for linear infinite-dimensional systems widely studied
-techniques used typically extensions of luenberger observers used for finite-dimensional systems.
-simplified approach: use spatial discretisation such as finite different/finite element to reduce infinite-dimensional to finite-dimensional observer. [1, 2]
-better to design infinite-dimensional observer and only discretise for numerical implementation. [3, 4, 5] **TODO:** *describe these design methods.*
nonlinear:
-no universal approach for observer design for infinite-dimensional nonlinear systems
-some methods for special case - infinite dimensional bilinear systems. [6, 7]
-for finite-dimensional nonlinear systems, common design methods are: linearisation (ie EKF), lyapunov method, sliding mode, high gain

1.1.2 symmetry preserving observers

1.1.2.1 early work

1.1.2.2 bonnabel et al

1.1.2.3 trumpf, mahony et al

1.1.2.4 juan's work - in detail

1.2 Theoretical Background

1.2.1 Rigid Body Dynamics

1.2.1.1 Lie Groups

Lie groups
The theory of Lie groups is required in the modelling of rigid bodies. A Lie group **G** is a group that is also a differentiable manifold. As a group, G satisfies the 4 group axioms: closure, associativity, identity, inverse. Because G is a differentiable manifold, in a neighbourhood of the identity it approximates euclidean space and allows ...?

Matrix Lie groups This work will be limited to matrix Lie groups, whose members are $n \times n$ matrices.

Lie algebra
Tangent space of Lie group with origin at identity is called Lie algebra $\mathfrak{g}$ of the group. It is called the Lie *algebra* because it has a binary operation, known as the Lie bracket $[X, Y]$. For matrix Lie groups, $[A, B] \stackrel{\triangle}{=} AB - BA$. Relationship to group operation, commutative & non-commutative, Baker-Campbell-Hausdorff formula...

Exponential map
exponential map - Lie group generators

Adjoint map
adjoint map & adjoint representation

Actions

1.2.1.2 SO(3)

Group elements

Lie algebra

Actions

Adjoint map

Rotation representation
A rotation represents the motion of a rigid body about a fixed point. In $\mathbb{R}^3$ this is an isometry (a transformation that preserves distances between any pair of points) that has a determinant of +1 (proper isometries). The set

of all proper orthogonal transformations is known as the *special orthogonal group* $\mathbf{SO}(3)$.

A rotation about a point in $\mathbb{R}^3$ can be represented by: **TODO:** *go into more detail on below*

rotation matrix:
3×3 matrix where magnitude of each column is 1, columns are orthogonal, determinant is $+1$.

scaled axis angle:
3-vector where direction represents axis of rotation and magnitude represents angle of rotation.

quaternions: 4-vector, same information as axis angle, but different form.

1.2.1.3 SE(3)

3D space - $\mathbb{R}^3$
In practice, robot, sensor, environment exist in 3D Euclidean space - $\mathbb{R}^3$. An arbitrary function that maps a pose *(or point?) in $\mathbb{R}^3$ to another can be defined as:

$$f : \mathbb{R}^3 \to \mathbb{R}^3 \tag{1.1}$$

To represent rigid bodies, require mappings corresponding to rotation and translation. Translation can be modelled as a function on a vector space $\mathbb{R}^3$ but the set of all rotations in $\mathbb{R}^3$ forms a Lie group.

homogeneous representation
4×4 screw matrix - represent rotation and translation with a single matrix of form:

$$\begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} \tag{1.2}$$

TODO: align the R and 0!!!!

To apply a rigid transformation to a point $\mathbf{p} = (x, y, z)$ in $\mathbb{R}^3$, represent with homogeneous coordinates. ie

$$\mathbf{p} = \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \tag{1.3}$$

SE(3)
-elements of group

$$\begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} \tag{1.4}$$

-lie algebra

$$\begin{bmatrix} [\omega]_\times & \mathbf{v} \\ \mathbf{0}_{1\times 3} & 0 \end{bmatrix} \tag{1.5}$$

-actions
-adjoint map & adjoint representation

1.2.1.4 Reference Frames

A reference frame is a system used to define a point on a manifold, on this case the Euclidean space $\mathbb{R}^3$. A reference frame is represented by an element of $\mathbf{SE}(3)$.
${}^A_B\mathbf{X}_C$ defines transformation of C w.r.t. B defined in A

Definition: Pose

Definition: point -homogeneous coordinates

Inverse

$$({}^A_B\mathbf{X}_C)^{-1} = {}^A_C\mathbf{X}_B \tag{1.6}$$

Transform point from one reference frame to another:

$${}^A_A\mathbf{p}_B = {}^A_A\mathbf{X}_B {}^B_A\mathbf{p}_B \tag{1.7}$$

$${}^B_A\mathbf{p}_B = {}^B_B\mathbf{X}_A {}^A_A\mathbf{p}_B \tag{1.8}$$

Transform pose from one reference frame to another -change of basis

$${}^B_C\mathbf{X}_D = ({}^B_B\mathbf{X}_A) {}^A_C\mathbf{X}_D ({}^B_B\mathbf{X}_A)^{-1} \tag{1.9}$$

1.2.1.5 Robot State Representation

-inertial frame A, sensor/robot frame B -p,v,a,R,omega,alpha - define, state reference frames
position ${}^A_A\mathbf{p}_B$
velocity ${}^B_A\mathbf{v}_B$
acceleration ${}^B_A\mathbf{a}_B$
orientation ${}^A_A\mathbf{R}_B$ - rotation matrix
angular velocity ${}^B_A\omega_B$ - scaled axis representation

angular acceleration ${}^{B}_{A}\alpha_B$ - scaled axis representation

pose of robot w.r.t. inertial frame, defined in inertial frame ie. screw matrix:

$$ {}^{A}_{A}\mathbf{S}_B(t) = \begin{bmatrix} {}^{A}_{A}\mathbf{R}_B(t) & {}^{A}_{A}\mathbf{p}_B(t) \\ \mathbf{0}_{1\times 3} & 1 \end{bmatrix} \tag{1.10} $$

velocity (linear and angular) w.r.t. inertial frame, defined in body frame ie. twist matrix:

$$ {}^{B}_{A}\mathbf{T}_B(t) = \begin{bmatrix} [{}^{B}_{A}\omega_B(t)]_\times & {}^{B}_{A}\mathbf{v}_B(t) \\ \mathbf{0}_{1\times 3} & 0 \end{bmatrix} \tag{1.11} $$

acceleration (linear and angular) w.r.t. inertial frame, defined in body frame ie. wrench matrix

$$ {}^{B}_{A}\mathbf{W}_B(t) = \begin{bmatrix} [{}^{B}_{A}\alpha_B(t)]_\times & {}^{B}_{A}\mathbf{a}_B(t) \\ \mathbf{0}_{1\times 3} & 0 \end{bmatrix} \tag{1.12} $$

1.2.1.6 Robot Dynamic Model

screw matrix:
$\frac{\mathrm{d}}{\mathrm{d}t}\mathbf{S}(t) = \mathbf{S}(t)\mathbf{T}(t)$
numerically: $\mathbf{S}(t+\delta t) = \mathbf{S}(t)e^{\delta t \mathbf{T}(t)}$

twist matrix:
$\frac{\mathrm{d}}{\mathrm{d}t}\mathbf{T}(t) = \mathbf{W}(t)$
numerically: $\mathbf{T}(t+\delta t) = \mathbf{T}(t) + \delta t \mathbf{W}(t)$

wrench matrix:
$\frac{\mathrm{d}}{\mathrm{d}t}\mathbf{W}(t) = 0$
numerically: $\mathbf{W}(t+\delta t) = \mathbf{W}(t)$
-update methods (euler, runge-kutta etc)

1.2.1.7 Sensor State Representation

1.2.1.8 Sensor Dynamic Model

-ODEs (same as robot + scanning)
-parameters ie FOV, steps

1.2.2 Symmetry Preserving Observers

1.2.2.1 definitions?

1.2.2.2 construction, ie moving frame method etc

1.2.3 Infinite Dimensional Observers

1.2.4 Discretisation Methods?

1.3 Problem Statement

context: Advances in hardware and manufacturing have made autonomous and semi-autonomous robots more available. Use in industry and even general public has increased. Full autonomous robots are still limited to structured environments and tasks such as in factories and warehouses. Before robots can operate autonomously in unstructured environments, new sensor models are required to more effectively observe and represent complex environment states. **TODO:** *Why are new sensor models required? Check if this is covered in literature review. If not, need to expand on this.*

problem/lacking: One method of estimating the state of the environment is to use a state observer. The majority of observer implementations do not take into account the natural symmetries of the dynamics of the state. Doing so has shown to be beneficial in both the design of observers, and improved convergence properties. However, these invariant observer methods are still limited to finite dimensional systems. In many implementations involving infinite-dimensional systems, the system is discretised to a finite dimensional one prior to observer design. **TODO:** *How does this influence performance?*

What is needed is a theory of infinite dimensional, symmetry preserving observers, + design principles.

what will this theory provide?: This theory will simplify invariant observer design for infinite dimensional systems. Only discretising after observer design will maximise the potential of dense sensors. This will allow for more accurate and fast estimation of complex environments,

approach: This project aims to develop some of this theory. The approach taken will be to design an invariant observer for a specific infinite dimensional system, before generalising the results.

estimation problem - cube pose & size: The environment the robot is moving throughout consists of a room (rectangular prism) + cube; each of unknown size and pose. Attached to the robot is a 2D laser rangefinder. Using depth measurements from this sensor, the observer must estimate the size and pose of the cube. It is assumed that the room is stationary and the cube has constant angular and linear acceleration.
TODO: *Diagram*
TODO: *Precise mathematical description of problem*

deliverables:
The primary deliverable of this project is the observer design and simulation. Will later try to develop some general theory from this specific case. Will validate simulation with experiment using Hokuyo UBG 04-LX sensor,

??? robot arms and cubes of various sizes and materials. **TODO:** *More detail, + be careful about what you promise*

Chapter 2

Theory Results

Chapter 3

Simulation

3.1 Implementation

3.1.1 Sensor modelling

3.1.2 Environment modelling

3.1.3 Measurement modelling

3.1.4 Observer

3.2 Results

Chapter 4

Experiment

Chapter 5

Conclusion

Bibliography

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