Robotics Notes

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Contents

Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CV	Computer Vision
RL	Reinforcement Learning
prob.	probability
params.	parameters
info.	information
a.k.a.	also known as
func.	function
vs.	versus
CNN	Convolutional Neural Network
GNN	Graph Neural Network
GAN	Generative Adversarial Network
DOF	degrees of freedom
EE	end-effector
D-H	Denavit–Hartenberg
KF	Kalman Filter
EKF	Extended Kalman Filter
IF	Information Filter
EIF	Extended Information Filter
MHEKF	Multi-Hypothesis Extended Kalman Filter

1 Introduction

This is my personal learning notes for robotics.

1.1 Learning Resources

- Springer Gandbook of Robotics [SKK08]
- Probalistic Robotics [TBF06]

[**TODO:**]

2 Robotics Foundations

2.1 Introduction

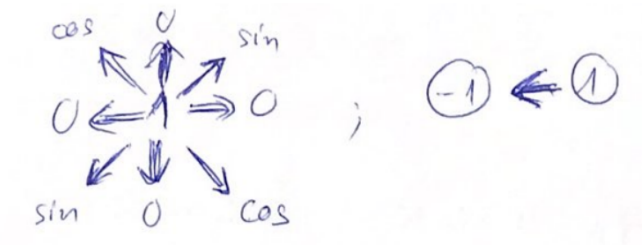
Types of robots:

Types	Articulated robot	Gantry	Scara	Delta	Hexapod
Workspace	Large			Small	Small
Structure	6 rotational	3 linear	1 translational, 2-3 parallel rotational	3 parallel kinematics chains	6 parallel kinematics chains
Market share	68%	19%	11%	1%	1%

2.2 DH Convention

Denavit–Hartenberg (D-H) Convention: [**TODO:**]

Elementary rotation matrices:



2.3 Position & Orientation

- Euler angles: **12** different sets of angles $R_{xy'z''}(\Phi) = R_z(\varphi)R_{y'}(\theta)R_{z''}(\psi)$
- Roll-Pitch-Yaw: fixed frame XYZ $R(\varphi, \theta, \psi) = R_z(\varphi)R_y(\theta)R_x(\psi)$
- Gimbal lock: loss of 1 degrees of freedom (DOF) in a 3-dimensional, 3 gimbal mechanism when 2/3 gimbals are driven into a parallel configuration
  NOTE: It exists no matter what rotation sequence you choose

- Angle & axix representation: solves gimbal lock problem
  However, does not guarantee an unique solution. When doing inverse, has problem when $\sin\theta = 0$
- Unit quaternion: ***CAN*** describe any rotation without ambiguities!

Intuition: angle & axis representation, unit quaternion are ways to avoid dealing with/or deal better with gimbal lock

2.4 Actuators and Joints

2.5 Workspace

2.6 Kinematics

2.6.1 Direct Kinematics

- Homogeneous coordinate representation, transformation matrix
- $\vec{e}_{x,^io} = \vec{e}_{z,^{i-1}o} \times \vec{e}_{z,^io}$

2.6.2 Inverse Kinematics

- Kinematic redundancy: No → Functional → hyper
- 3 ways to solve:
  - Analytical: if analytical solution exists, ***ALWAYS*** use it. Non redundant
  - Numerical: If closed-form solution does not exist / too hard to find analytically. If redundant

$$err = r_d - f(q_e)$$
$$q_{k+1} = q_k + \frac{1}{J_A(q)} adj(J_A(q)) err_k$$

  - Algebraic: solve polynomials equations

2.6.3 Differential Kinematics

joint velocity ⇒ end-effector (EE) velocity

Using Geometric Jacobian

$$q = [q_1 \dots q_n]^T \quad \text{– joint positions} \tag{2.1}$$

$$v_E = \begin{bmatrix} \dot{p}_E \\ \omega_E \end{bmatrix} \quad \text{– EE velocity} \tag{2.2}$$

$$\dot{p}_E = [\dot{p}_x \quad \dot{p}_y \quad \dot{p}_z]^T \quad \text{– EE linear velocity} \tag{2.3}$$

$$\omega_E = [\omega_x \quad \omega_y \quad \omega_z]^T \quad \text{– EE angular velocity} \tag{2.4}$$

$$\Rightarrow v_E = J_G(q).\dot{q} \tag{2.5}$$

$$J_G(q) = \begin{bmatrix} J_{GP}(q) \\ J_{GO}(q) \end{bmatrix} \quad \begin{array}{l} -\text{Geometric Jacobian} \\ J_{GP}(q) - \text{geometric position Jacobian} \\ J_{GO}(q) - \text{geometric orientation Jacobian} \end{array} \tag{2.6}$$

Using Velocity Composition Rule

- Linear velocity composition rule

$$^{O}\dot{r}_{p,^{0}O} = \tag{2.7}$$

- Angular velocity composition rule
- Strictly follow D-H conventions, then $\Rightarrow \delta, d, l, \alpha, \theta$
  Prismatic joints, revolute joints

2.6.4 Kinematics Singularities

Kinematics singularities occurs if the Jacobian is rank-deficient. There are 2 types:

- Boundary singularities: manipulator is out stretched or retracted $\Rightarrow$ does not drive the robot to the edge
- Internal singularities: caused by alignment of 2/more axes

Singularity affects the kinematics solution:

- Mobility of robotic structure is reduced
- Inverse kinematics $\Rightarrow$ yields infinite solutions
- Close to a singularity, small velocity in operational space **CAUSES** large velocity in joint space

[TODO: Singularities decoupling $\star$**]**

2.6.5 Kinematic Redundancy

2.6.6 Differential Mapping

2.6.7 Inverse Differential Kinematics

2.6.8 Statics

2.6.9 Manipulability Ellipsoids

2.7 Dynamics Model

2.8 Dynamic Parameter Identification

2.9 Direct & Inverse Dynamics

2.10 Parallel Kinematics

3 Trajectory Planning

3.1 Introduction

3.1.1 Definitions

Goal: compute a function of time that describes the motion of robot's joints. Depending on the task and time constraints, there will be different restrictions on the trajectory.

- A **Path** is a set of points in the joint/operational space, as geometrical description of the motion
- A **Trajectory** is a path through space as a function of time
  Trajectory = Path + Time Law

3.1.2 Joint space vs. Operational Space Trajectory Planning

- Joint space: planning is done in terms of joint positions, velocities and accelerations: $q, \dot{q}, \ddot{q}$. $\Rightarrow$ trajectory of the EE should NOT be important.
- Operational space: planning is done in terms of EE positions, orientation and their derivatives: $\mathbf{x}_E, \dot{\mathbf{x}}_E, \ddot{\mathbf{x}}_E$. This gives more control over the EE path, e.g., for melding, gluing applications.

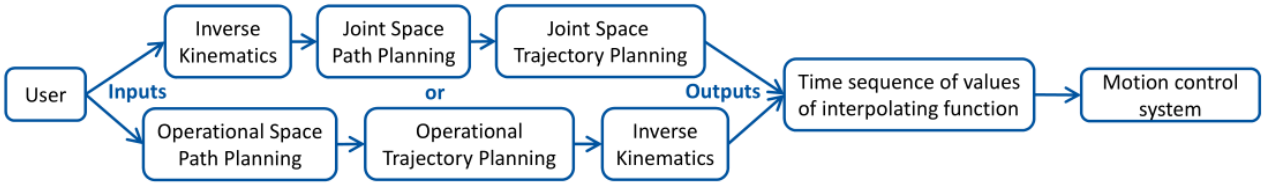


Figure 3.1: Trajectory planning procedure.

- Inputs: path description, geometric / kinematic constraints (usually in operational space), constraints resulting from the manipulator dynamics
- Outputs: A time sequence of values for the joints' positions, velocities and accelerations as needed by the motion control system
- The paths and trajectories are not defined by the user explicitly in each point, but as a set of relevant parameters (params.): start, end points, possible intermediate points, geometric primitives, total time, maximum accelerations and velocities

3.2 Joint Space Trajectories

Given start and end EE poses $\mathbf{P}_{start}, \mathbf{P}_{end}$ (and possible intermediate poses), apply inverse kinematics to get the joint poses (Fig. 3.1).

$$\left.\begin{array}{l}\mathbf{P}_{start} \Rightarrow \mathbf{q}(t_{start}) \\ \mathbf{P}_{end} \Rightarrow \mathbf{q}(t_{end})\end{array}\right\} \Rightarrow \mathbf{q}_t, \dot{\mathbf{q}}_t, \ddot{\mathbf{q}}_t \quad \text{for} \quad t \in [t_{start}, t_{end}]$$

3.2.1 Point-to-Point Motion

Possible ***timing laws*** for point-to-point motion:

- Cubic polynomial for the joints motion: can impose start, end positions and velocities

  $q_i(t) = a_{i,3}t^3 + a_{i,2}t^2 + a_{i,1}t + a_{i,0}$ – cubic polynomial for joint i motion

  $\dot{q}_i(t) = 3a_{i,3}t^2 + 2a_{i,2}t + a_{i,1}$ – parabolic velocity profile

  $\ddot{q}_i(t) = 6a_{i,3}t + 2a_{i,2}$ – linear acceleration profile

  Problem: infinite jerk at start and end positions

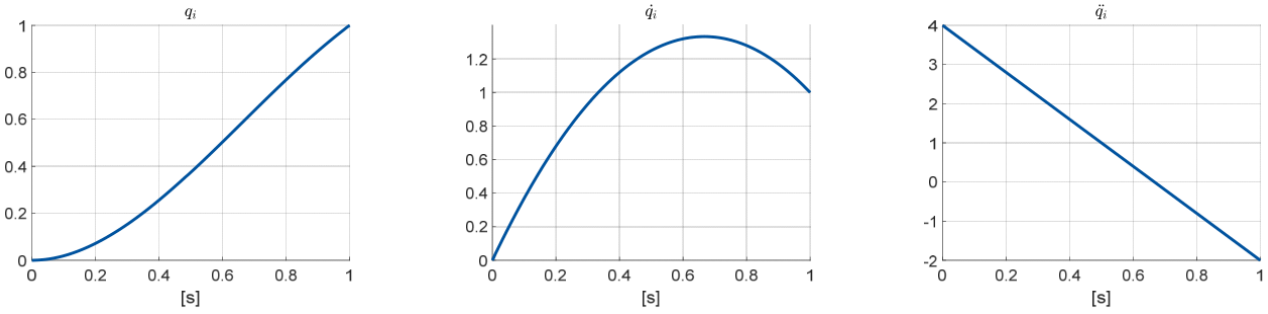


Figure 3.2: Example of cubic polynomial.

- Fifth order polynomial for the joints motion: allows imposing start, end positions, velocities and accelerations with finite jerk.

  $q_i(t) = a_{i,5}t^5 + a_{i,4}t^4 + a_{i,3}t^3 + a_{i,2}t^2 + a_{i,1}t + a_{i,0}$ – fifth order polynomial

  $\dot{q}_i(t) = 5a_{i,5}t^4 + 4a_{i,4}t^3 + 3a_{i,3}t^2 + 2a_{i,2}t + a_{i,1}$ – forth order velocity profile

  $\ddot{q}_i(t) = 20a_{i,5}t^3 + 12a_{i,4}t^2 + 6a_{i,3}t + 2a_{i,2}$ – cubic acceleration profile

- Trapezoidal acceleration profile: given time period, max acceleration, velocity and position. **NOTE:** Just know that the below formulas and constraints exist. The derivation is

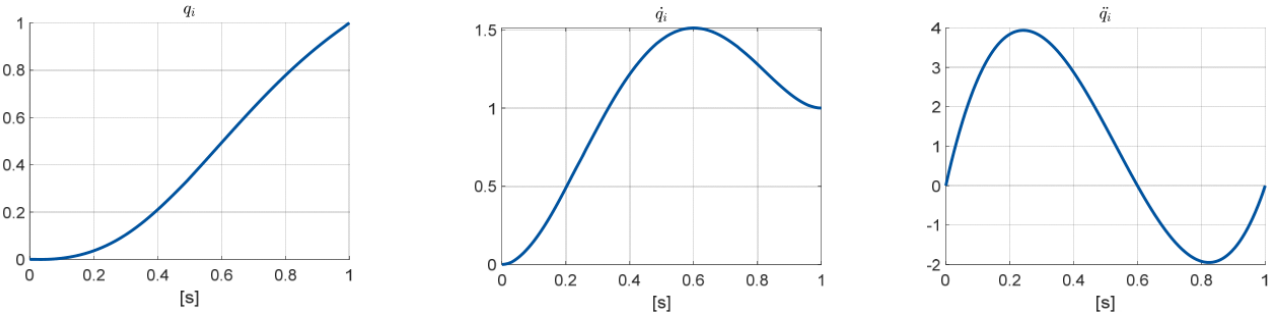


Figure 3.3: Example of fifth order polynomial.

complicated and time-consuming.

$$\Delta t_{i,I} = T - \frac{\dot{q}_{\max}}{\ddot{q}_{\max}} - \frac{q_{\max}}{\dot{q}_{\max}} \qquad \frac{q_{\max}}{T} \leq \dot{q}_{\max} \leq \frac{2q_{\max}}{T}$$

$$\Delta t_{i,II} = 2\frac{\dot{q}_{\max}}{\ddot{q}_{\max}} + \frac{q_{\max}}{\dot{q}_{\max}} - T \qquad \frac{\dot{q}_{\max}}{T - \frac{q_{\max}}{\dot{q}_{\max}}} \leq \ddot{q}_{\max} \leq \frac{2\dot{q}_{\max}}{T - \frac{q_{\max}}{\dot{q}_{\max}}}$$

$$\Delta t_{i,IV} = T - 4\Delta t_{i,I} - 2\Delta t_{i,II} \qquad \ddot{q}_{\max} = \frac{\ddot{q}_{\max}}{\Delta t_{i,I}} = \frac{\ddot{q}_{\max}}{T - \frac{\dot{q}_{\max}}{\ddot{q}_{\max}} - \frac{q_{\max}}{\dot{q}_{\max}}}$$

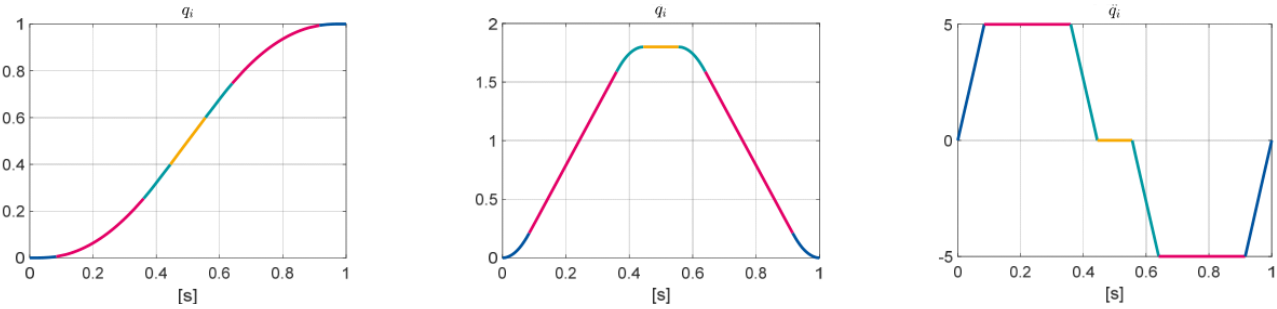


Figure 3.4: Example of trapezoidal acceleration profile.

3.2.2 Motion through a Sequence of Points

- This can be viewed as extension of point-to-point motion
- The path is defined through a **sequence of N path points**
- The time instances when these points must be reached should also be given
- Instead of using an $(N+3)$-order polynomial through N joint configurations, we can use low-order interpolating polynomials (Fig. 3.5).
  - Each joint variable q_i corresponds to a set of $N-1$ cubic polynomials $\Pi_{i,k}(t), k = 1, \ldots, N-1$

$$q_i(t_k) = q_{i,k} \qquad \text{– intermediate poses}$$
$$q_{i,1} = q_{i,start}, q_{i,N} = q_{i,end}$$
$$t_{i,1} = t_{i,start}, t_{i,N} = t_{i,end}$$
$$\Pi_{i,k}(t_k) = \Pi_{i,k+1}(t_k) = q_{i,k} \qquad \text{– path continuity}$$

- To impose **velocity continuity**, additional information is needed

  $$\dot{\Pi}_{i,k}(t_{i,k+1}) = \dot{\Pi}_{i,k+1}(t_{i,k+1}) = \dot{q}_i(t_{i,k+1})$$

  – Arbitrary values for the velocity at the path points $\dot{q}_i(t_k)$ **or**
  – Values for the velocity at the path points $\dot{q}_i(t_k)$ according to some criteria **or**
  – Impose continuous acceleration at the path points

  NOTE: Probably leads to acceleration jerks
- Continuity for acceleration: imposed by 4 equations

  NOTE: Required using 2 additional virtual points for 2 additional polynomials $\Rightarrow 4(N+1)$ equations for $4(N+1)$ unknowns. It is computationally expensive. With some tricks, the problem can be reduced to N variables ...

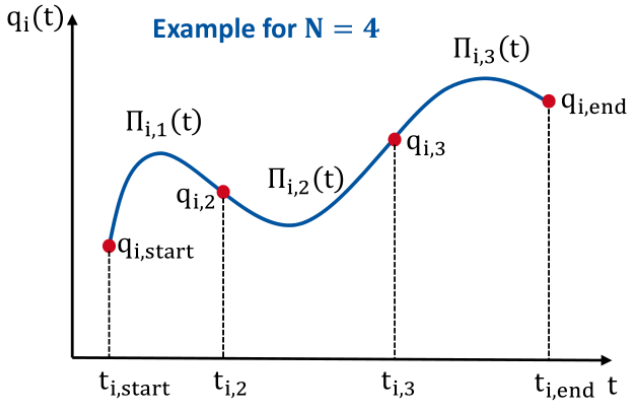


Figure 3.5: Example of motion through sequence of four points using low-order (cubic) interpolating polynomials.

3.3 Operational-space Trajectories

- Planning in the Joint Space may result in unexpected EE motion, resulting from the non-linear direct kinematics.
- Planning in Operational Space ensures that the EE motion follows exactly the geometrically specified path by
  – interpolating a sequence of prescribed poses
  – generating analytical motion primitives (e.g. lines, circular arcs etc.)
  – but it requires **real time** inverse kinematic computation, which is more computationally expensive

- Path primitives + timing laws = trajectory planning
  analyzed and computed separately

3.3.1 Path primitive

- The word *primitive* means a basic component, from which other is derived.
- **Path primitives** are the analytical geometrical descriptions for paths.
- Parametric representation of the path Γ in space is a function of a general parameter σ describe the position vector for point $\mathbf{P}$ (Fig. 3.6)

$$\mathbf{r}_{\mathbf{P},^jO} = \mathbf{r}_\mathbf{P} = \mathbf{r}_\mathbf{P}(\sigma), \quad \sigma \in [\sigma_{start}, \sigma_{end}]$$

- Usually it makes sense to replace general params. σ by the current path length s

$$\mathbf{r}_\mathbf{P}(s) = f(s) \quad \text{with} \quad \sigma_{start} = 0, \sigma_{end} = s_{end}$$

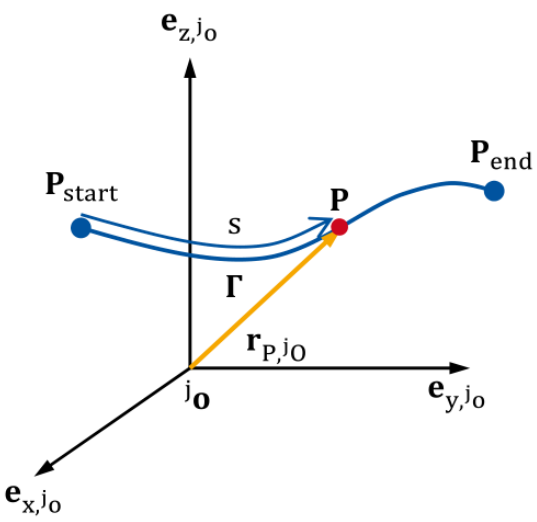


Figure 3.6: Example for parametric representation of path Γ

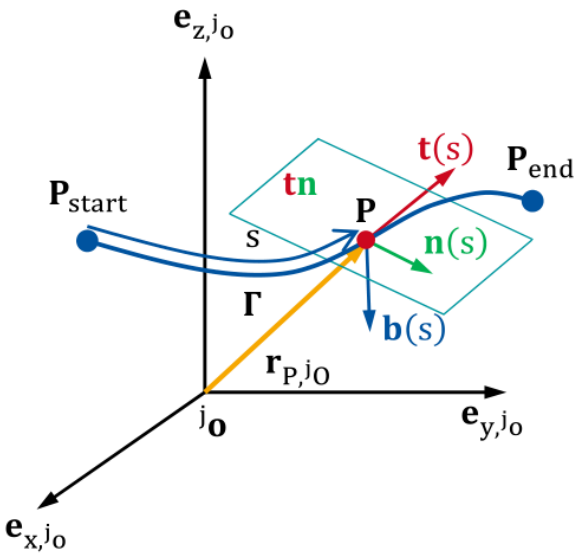


Figure 3.7: Frenet frame with 3 unit vectors.

3.3.2 Frenet Frame

Frenet Frame is used to define the coordinate orientation along the path Γ. The three unit vectors establish the Frenet frame (Fig. 3.7):

- Tangent unit vector $\mathbf{t}(s) = \dfrac{d\mathbf{r}_P(s)}{ds}$ along the direction of the path
- Normal unit vector $\mathbf{n}(s) = \dfrac{1}{\left\|\frac{d^2\mathbf{r}_P(s)}{ds^2}\right\|}\dfrac{d^2\mathbf{r}_P(s)}{ds^2}$ perpendicular to $\mathbf{t}(s)$
- Binormal unit vector $\mathbf{b}(s) = \mathbf{t}(s) \times \mathbf{n}(s)$ complements a right handed moving frame

3.3.3 Path Primitive: Rectilinear Path

The simplest parametric path representation is a linear segment between $\mathbf{P}_{start}$ and $\mathbf{P}_{end}$

$$\mathbf{r}_{P,{}^jO}(s) = \mathbf{r}_{P_{start},{}^jO} + \frac{s}{\left\|\mathbf{r}_{P_{end},{}^jO} - \mathbf{r}_{P_{start},{}^jO}\right\|}\left(\mathbf{r}_{P_{end},{}^jO} - \mathbf{r}_{P_{start},{}^jO}\right) \tag{3.1}$$

$$\mathbf{t}(s) = \frac{d\mathbf{r}_P(s)}{ds} = \frac{1}{\left\|\mathbf{r}_{P_{end},{}^jO} - \mathbf{r}_{P_{start},{}^jO}\right\|}\left(\mathbf{r}_{P_{end},{}^jO} - \mathbf{r}_{P_{start},{}^jO}\right) \tag{3.2}$$

$$\mathbf{n}(s) = \frac{1}{\left\|\frac{d^2\mathbf{r}_P(s)}{ds^2}\right\|}\frac{d^2\mathbf{r}_P(s)}{ds^2} \quad \text{with} \quad \frac{d^2\mathbf{r}_{P,{}^jO}(s)}{ds^2} = 0 \tag{3.3}$$

$\Rightarrow$ **CAN NOT** define the Frenet frame uniquely. The plane **tn** can be rotated arbitrarily around $\mathbf{t}(s)$

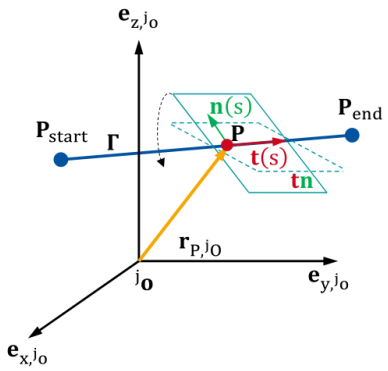
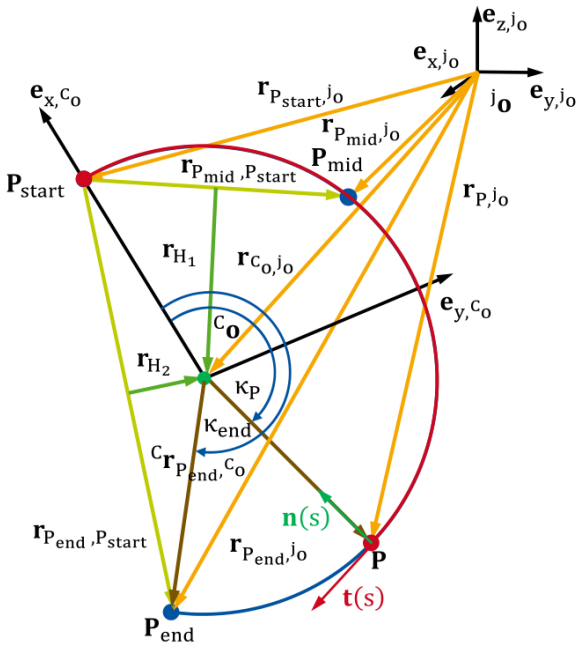


Figure 3.8: Rectilinear path primitive.

3.3.4 Path Primitive: Circular Arc

The circular arc is defined through three points $\mathbf{P}_{start}$, $\mathbf{P}_{mid}$ and $\mathbf{P}_{end}$.

- Compute center ${}^j\mathbf{r}_{C_O,{}^jO}$
  - Determine ${}^j\mathbf{r}_{P_{mid},P_{start}}$
  - Determine ${}^j\mathbf{r}_{P_{end},P_{start}}$
  - Determine unit vector ${}^j\mathbf{e}_{z,{}^cO}$
  - Determine helper vectors $\mathbf{r}_{H_1}, \mathbf{r}_{H_2}$
  - Determine ${}^j\mathbf{r}_{C_O,{}^jO}$
- Determine unit vectors ${}^j\mathbf{e}_{x,{}^cO}, {}^j\mathbf{e}_{y,{}^cO}$
- Determine radius
- ...



3.3.5 Path Primitive: Spline Path

Given a set of points $\mathbf{P}_i$ for $i \in \{1, n\}$, a smooth curves is generated by interpolating method

- Between two consecutive points $\mathbf{P}_i$ and $\mathbf{P}_{i+1}$, there is path segment $\mathbf{S}_i(\lambda)$
- To ensure smoothness between path's segments, the path must be continuous up to its second derivative at path points
- Use polynomials of degree five

$$\mathbf{S}_i(\lambda) = a_{i,5}\lambda^5 + a_{i,4}\lambda^4 + a_{i,3}\lambda^3 + a_{i,2}\lambda^2 + a_{i,1}\lambda + a_{i,0}, \qquad 0 \le \lambda \le \lambda_i$$

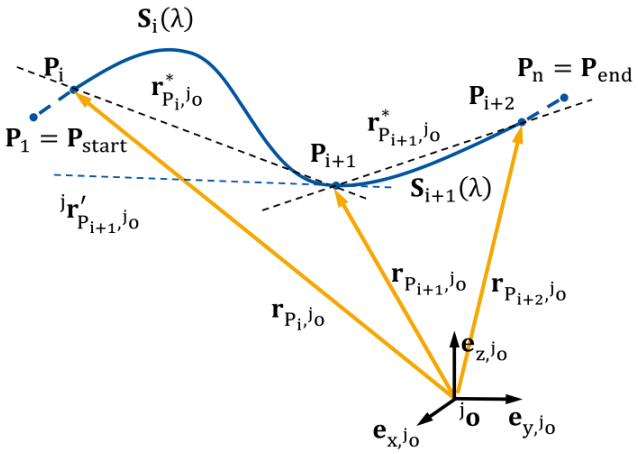


Figure 3.9: Spline path primitive.

3.4 Nonlinear Dynamics Motor Primitives

This *nonlinear dynamics motor primitives* are NOT the same as path primitives mentioned above. Let's examine two second-order dynamic systems (z, y) and (v, x) as follows: [INS02]

$$\dot{z} = f_z(y, z) = \alpha_z(\beta_z(g - y) - z) \tag{3.4}$$

$$\dot{y} = f_y(z, x, v) = z + \frac{\sum_{i=1}^{N} \Psi_i w_i}{\sum_{i=1}^{N} \Psi_i} v \tag{3.5}$$

$$\dot{v} = f_v(x, v) = \alpha_v(\beta_v(g - x) - v) \tag{3.6}$$

$$\dot{x} = f_x(v) = v \tag{3.7}$$

$$\Psi_i = \exp\left(-\frac{1}{2\sigma_i^2}(\tilde{x} - c_i)^2\right), \quad i = 1, \ldots, N \qquad \text{– Gaussian kernel functions} \tag{3.8}$$

$$\tilde{x} = \frac{x - x_0}{g - x_0} \tag{3.9}$$

- The 2nd system dynamic behavior is simply analogous to value tracking: variable x goes to target value g, the velocity v starts and ends at 0 (Fig. 3.11).
- Compared to the 2nd one, the 1st system is just different in the extra nonlinear term in $\dot{y}$

- This is similar as with Fourier series. Fourier series is used to approximate an arbitrary time series data via a weighted sum of multiple sinusoidal functions. Here, we approximate the different between the velocity profile for trajectory tracking and for value tracking by a weighted sum of Gaussian-like functions.
- The above dynamical system is spatially invariant in the sense that scaling of the goal g does not affect the topology of the attractor landscape

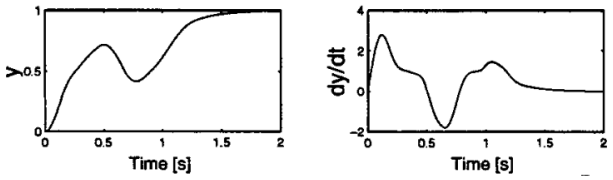


Figure 3.10: Trajectory tracking: y as joint position and velocity profile $\dot{y}$.

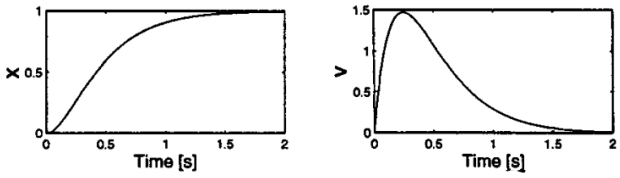


Figure 3.11: Value tracking: x as joint position and velocity profile $\dot{x}$.

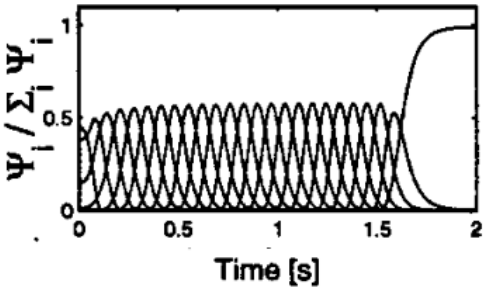


Figure 3.12: Basis functions from Gaussian kernels.

With regards to trajectory planning, long story short, we manage to parameterize a trajectory y to params. w_i

- q - current joint position
- g - desired joint position
- x - a timing signal
- v - a scaling signal

Given a new trajectory:

- Shift the given trajectory to 0 start position
- Scale the time constants of the dynamical system such that (v, x) reaches $(0, g)$ at approximately the same time $\Rightarrow$ a time trajectory for $v(t), x(t)$
- Given $v(t), x(t)$, calculate $u_{des} = \dot{y}_{demo} - z$ as desired output
- Learn w_i via recursive least squares to minimize the locally weighted error criterion for each local model $u_{i,t} = w_i v_t$

$$J_i = \sum_t \Psi_{i,t}(u_{des,t} - u_{i,t})^2$$

This parameterization approach satisfies following requirements:

- Able to fit a demonstrated trajectories with high precision (fitting all DOF and all points of the trajectories)
- Able to generate similar movements to different goals. If we fix the weights w_i, change the goal g, we will receive a similar trajectories. **NOTE:** good with close targets, better with variation in height, not with left and right.
- Robust against perturbations (e.g., in scenarios there is interaction with external objects)

$$\tilde{y} \qquad \text{– the actual position} \tag{3.10}$$

$$\dot{y} = \alpha_y \left(\frac{\sum_{i=1}^{N} \Psi_i, w_i}{\sum_{i=1}^{N} \Psi_i} v + z \right) + \alpha_{py}(\tilde{y} - y) \tag{3.11}$$

$$\dot{x} = v \left(1 + \alpha_{px}(\tilde{y} - y)^2\right)^{-1} \tag{3.12}$$

- Good basis for comparing movements, as a metric for measuring differences between movements. Similar movements will have similar weights $w_i \Rightarrow$ can be used to classify movements (simple nearest neighbors)

[TODO: The effect of hyper-params.]

- α_v
- β_v
- α_z
- β_z
- c_i
- ...

4 Robotics System Engineering

4.1 Structural Synthesis

4.2 End-Effector Technology

4.3 Components of Robotics System

4.4 Control Architecture

4.5 Mobile Manipulators

5 Robotics Sensor Systems

This chapter gives an overview on different types of sensors used in robotic systems, the physics behind them and more ...

5.1 Overview

Two classes of sensors:

Proprioceptive sensors	Exteroceptive sensors
Proprioception, also referred to as *kinaesthesia*, is the sense of self-movement, force, and body position (src).	*Exteroception* is sensitivity to stimuli that are outside the body, resulting from the response of specialized sensory cells to objects and occurrences in the external environment. Exteroception includes the five senses of sight, smell, hearing, touch, and taste (src).
Proprioceptive sensors provide internal perception about the state of the robot, i.e., joint positions, velocities, accelerations, torque.	*Exteroceptive* sensors provide external perception about the measured force, tactile input, proximity range, vision, etc.

5.1.1 Future Applications

- Industrial robots: more complex tasks, wider / broader range of manufacturing
- Service robots: excluding industrial automation application
- Application: logistics, medical, field, defense robots.

5.1.2 Key abilities

(CIMMPC)

- Configurability
- Interaction ability
- Motion ability
- Manipulation ability
- Perception ability: suitable choice of sensing modality
- Cognitive ability: reduction of programming and configuration effort

5.1.3 Key technologies

Advances in sensors: $\begin{cases} -\text{Control theory} \\ -\text{Safety} \\ -\text{Navigation} \end{cases}$

[TODO: add graph]

5.2 Control & Feedback Control Systems

5.2.1 Introduction to industrial robots

5.2.2 Internal metrology of industrial robot

5.2.3 External metrology of industrial robot

5.2.4 Communication between sensors & robots via industrial Ethernet & 5G

5.3 Electromagnetic Sensor

Proprioceptive sensors:

	Encoders	Tachometer	Gyroscope
Position/Pose	✓		
Velocity	✓	✓	
Acceleration	✓	✓	✓

NOTE: If you can measure x, you can derive $\dot{x}, \ddot{x}$

5.3.1 Principles of Electromagnetism

Maxwell's equations:

- Gauss's law

$$\Phi_E = \oint \vec{E}.d\vec{A} = \frac{Q_{encl}}{\varepsilon_0}; \varepsilon_0 = \text{const} \quad \Leftrightarrow \quad \vec{\nabla}\vec{E} = \frac{\rho}{\varepsilon_0} \tag{5.1}$$

$$\Leftrightarrow \oint \vec{D}.d\vec{A} = \int \rho.dV = Q_{encl}; \vec{D} = \varepsilon\vec{E} \quad \Leftrightarrow \quad \boxed{\vec{\nabla}\vec{D} = \rho} \tag{5.2}$$

with: Φ_E – electric flux

- Gauss's law for magnetism: $\vec{B}$ is solenoidal vector fields. There is no magnetic monopole [**TODO:**] **divergence, no source, no sink**

$$\Phi_B = \oint \vec{B}.d\vec{A} = 0 \quad \Leftrightarrow \quad \boxed{\vec{\nabla}\vec{B} = 0} \tag{5.3}$$

with: Φ_B – magnetic flux

- Maxwell-Faraday equation
- Ampere's circuital law
- Magnetic field
- Hall effect

5.3.2 Position Sensors

- Potentiometer: works according to Ohm's law

$$\begin{cases} \text{Turning} \\ \text{Sliding} \end{cases} \text{potentiometer: when the joint rotates, the gear turns the potentiometer}$$

- Induction-based sensors:
  - Resolver ...
  - Inductive transducer
  - Tranverse armature transducer: based on Maxwell's bridge
  - Differential transducer
  - Inductosyn
- Rotary encoders:
  - Absolutely Encoder versus (vs.) Incremental Encoder [**TODO: images**]

Absolutely Encoder	Incremental Encoder
maintain information (info.) when power is removed	immediately report position changes
position info. is available immediately	doesn't keep track
relationship between encoder value & physical position set at assembly	have to go back to fixed point to initialize measurement

  - Magnetic encoder vs. Optical encoder
  - Number of track $\Rightarrow$ resolution
    n tracks $\Rightarrow$ resolution $\frac{2\pi}{2_n}$

NOTE: Current robots use encoders (magnetic / optical).

	Advantages	Disadvantages
Potentiometer	Simple Low cost	Limited range & accuracy Wear out (due to contact)
Resolver	Non-contact	Analog, expensive Requires decoding circuit
Inductive Transducer	Non-contact High accuracy	limited range Analog
Magnetic encoder	Non-contact Robust	Required decoding usually lower resolution
Optical encoder	Non-contact	Required gray decoding Complex wiring

5.3.3 Speed Sensors

Maxwell-Faraday's equation:

$$\frac{\partial \vec{B}}{\partial t} \Rightarrow \frac{\partial \vec{E}}{\partial t}$$

5.3.4 Acceleration Sensors

- Mechanical gyroscopes **(conservation of angular momentum)**
- Micro electro-mechanical system gyroscope (MEMS)

5.4 Capacitive & Piezoelectric Sensors

5.5 Visual Electromagnetic Sensors

5.6 Thermoelectric & Ultrasonic Sensors

5.7 Machine Vision

5.8 Tactile Information

Types of robotic tactile sensors:

- Capacitive tactile sensors (Sec. 5.4)
- Piezoresistive tactile sensors (Sec. 5.4)
- Piezoelectric tactile sensors (Sec. 5.4)
- Inductive tactile sensors
- Optical-based tactile sensors

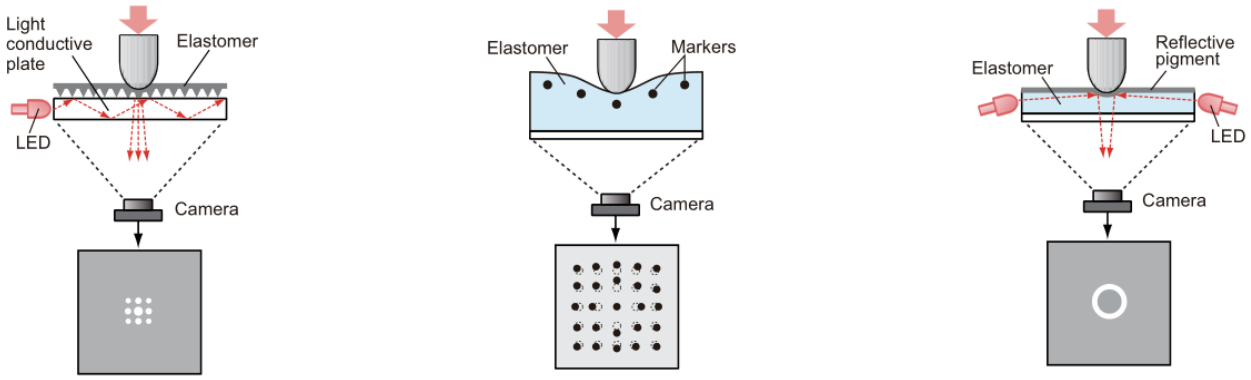


Figure 5.1: Types of optical-based tactile sensors: Light conductive plate, Marker displacement, Reflective membrane (from left to right) [Shi19].

- Strain gauges
- Audio-based tactile sensors: can provide information about surface texture.
- Multi-component tactile sensors

Prior works use tactile sensors in inference of object properties [LBD+17] and robotic manipulation [YA19].

- Grasping
  - Heuristic grasp adaptation strategy
  - Grasp adaptation with slip detection
  - Grasp adaptation with estimating friction coefficient
  - Grasp adaptation with grasp stability estimation
  - Complete grasp process with tactile sensing
- Other robotic manipulation
  - Detecting events with tactile sensors
  - Estimating pose and location with tactile sensors
  - Reinforcement learning with tactile sensors
  - Exploring the workspace without vision
- Tactile perception

Issues of introducing tactile sensors to robotic hands:

- Difficulty to install on robotic hands.
- Wiring, power supply, and processing.
- Low durability, fragility.
- Less compatibility with the other tactile sensors.
- It is unclear what we can do with tactile sensors.
- Disadvantages caused by tactile sensors.
  - Maintenance becomes complicated.

  - Programming becomes complicated.
- Expensive.
- Asking for the moon.

5.9 Data Acquisition & Sensor Fusion

5.10 Signal Preprocessing

5.11 Communication & Signal Transmission

5.11.1 Challenges in Data Transmission

- Different forms (text, speech, images)
- Large distances, limited time
- Certain bandwidth

5.11.2 Information Systems & Data Transmission Principles

5.11.3 Transmission Media

5.11.4 Network Topologies & Data Transmission Protocols

Topologies: −P2P
−Bus
−Fieldbus

Protocols: OSI and TCP/IP

5.11.5 Robot Communication with ROS

6 Probabilistic Robotics

Reference from the great book: [TBF06].

6.1 State Estimation

6.1.1 Bayes Filters

$bel(x_t) = p(x_t \mid z_{1:t}, u_{1:t})$	belief over a state
$\overline{bel}(x_t) = p(x_t \mid z_{1:t-1}, u_{1:t})$	a posterior (before adapt to z_t)
$\Rightarrow$ Calculating $bel(x_t)$ from $\overline{bel}(x_t)$	correction/measurement update

Bayes Filter Algorithm:

2 for all x_t do:

3 $\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1}) bel(x_{t-1}) dx$ prediction step

4 $bel(x_t) = \eta\, p(z_t \mid x_t)\, \overline{bel}(x_t)$ update step

$\Rightarrow$ Can only be implemented for very simple estimation problems, finite state space

Important assumption: Markov property (each state s a complete summary of the past)

Problem: can not be implemented on digital computers

The next subsections describe two Gaussian filters (Kalman Filter (KF) and Information Filter (IF)) and two extensions of them (Extended Kalman Filter (EKF) and Extended Information Filter (EIF)). The Gaussian filters have major advantage in computational cost, with the disadvantage of having assumption on uni-model distribution.

6.1.2 The Kalman Filter (KF)

- ***Learning Resources:*** www.bzarg.com
- For continuous space, not discrete or hybrid

- **Assumption:** posterior are Gaussians and Markov property

$p(x_t \mid u_t, x_{t-1})$	must be linear func. (linear system dynamics)
$p(z_t, x_t)$	also linear
$bel(x_0)$	initial belief must be Gaussian

$$
\begin{aligned}
x_t &= A_t x_{t-1} + B_t u_t + \varepsilon_t \\
p(x_t \mid u_t, x_{t-1}) &= \det(2\pi\Sigma_t)^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(x_t - A_t x_{t-1} - B_t u_t)^T R_t^{-1}(x_t - A_t x_{t-1} - B_t u_t)\right] \\
z_t &= C_t x_t + \delta_t \quad (= y) \\
p(z_t \mid x_t) &= \det(2\pi Q_t)^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(z_t - C_t x_t)^T Q_t^{-1}(z_t - C_t x_t)\right] \\
bel(x_0) = p(x_0) &= \det(2\pi\Sigma_0)^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(x_t - \mu_0)^T \Sigma_0^{-1}(x_t - \mu_0)\right]
\end{aligned}
$$

Kalman Filter Algorithm: $(\mu_{t-1}, \Sigma_{t-1}, u_t, z_t)$

2	$\overline{\mu}_t = A_t\mu_{t-1} + B_t u_t$		incorporate u_t - prediction step - $\mathcal{O}(n^2)$
3	$\overline{\Sigma}_t = A_t\Sigma_{t-1}A_t^T + R_t$		
4	$K_t = \overline{\Sigma}_t C_t^T \left(C_t\overline{\Sigma}_t C_t^T + Q_t\right)^{-1}$	(Kalman gain)	incorporate z_t - correction step - $\mathcal{O}(n^{2,8})$
5	$\mu_t = \overline{\mu}_t + K_t(z_t - C_t\overline{\mu}_t)$		
6	$\Sigma_t = (I - K_t C_t)\overline{\Sigma}_t$		
7	return μ_t, Σ_t	$\Rightarrow$ belief at time t	

$\Rightarrow$ quite computationally expensive, **everything are Gaussians**

6.1.3 Extended Kalman Filter (EKF)

Overcome the assumption on linearity by only approximate by Gaussians

$$
\begin{aligned}
x_t &= g(u_t, x_{t-1}) + \varepsilon_t \\
z_t &= h(x_t) + \delta_t
\end{aligned}
$$

$$
\begin{aligned}
g(u_t, x_{t-1}) &\approx g(u_t, \mu_{t-1}) + g'(u_t, \mu_{t-1})(x_t - \mu_{t-1}) \\
&= g(u_t, \mu_{t-1}) + G_t(x_t - \mu_{t-1}) \\
& g' \text{ is the Jacobian of state } (n \times n \text{ matrix}) \\
p(x_t|u_t, x_{t-1}) &\approx \det(2\pi R_t)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}[x_t - g(u_t, x_{t-1})]^T R_t^{-1}[x_t - g(u_t, x_{t-1})]\right\} \\
h(t) &\approx h(\overline{\mu}_t) + h'(\mu_t)(x_t - \mu_{t-1}) \\
&= h(\overline{\mu}_t) + H_t(x_t - \mu_{t-1}) \\
p(z_t|x_t) &= \det(2\pi Q_t)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}[z_t - h(x_t)]^T Q_t^{-1}[z_t - h(x_t)]\right\}
\end{aligned}
$$

Extended Kalman Filter Algorithm: $(\mu_{t-1}, \Sigma_{t-1}, u_t, z_t)$

2 $\quad \overline{\mu}_t = g(u_t, \mu_{t-1})$

3 $\quad \overline{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + R_t$

4 $\quad K_t = \overline{\Sigma}_t H_t^T \left(H_t \overline{\Sigma}_t H_t^T + Q_t\right)^{-1}$

5 $\quad \mu_t = \overline{\mu}_t + K_t[z_t - h(\overline{\mu}_t)]$

6 $\quad \Sigma_t = (I - K_t H_t)\overline{\Sigma}_t$

7 $\quad$ return μ_t, Σ_t

- Can extend EKF $\Rightarrow$ Multi-Hypothesis Extended Kalman Filter (MHEKF)
- EKF's performance depends on degree of nonlinearities and uncertainty
- Unscented KF and moments matching KF are better

6.1.4 Information Filter (IF)

- Moment representation: μ & Σ
- Canonical representation: ξ & Ω

  Information precision matrix: $\Omega = \Sigma^{-1}$; $\Sigma = \Omega^{-1}$

  Information vector: $\xi = \Sigma^{-1}\mu$; $\mu = \Omega^{-1}\xi$

$$
\begin{aligned}
p(x) &= \det(2\pi\Sigma)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right\} \\
&= \eta \exp\left\{-\frac{1}{2}x^T \Omega x + x^T \xi\right\}
\end{aligned}
$$

Information Filter Algorithm: $(\xi_{t-1}, \Omega_{t-1}, u_t, z_t)$

2 $\quad \overline{\Omega}_t = (A_t \Omega_{t-1}^{-1} A_t^T + R_t)^{-1}$
3 $\quad \overline{\xi}_t = \overline{\Omega}_t (A_t \Omega_{t-1}^{-1} \xi_{t-1} + B_t u_t)$
} $\mathcal{O}(n^{2,8})$

4 $\quad \Omega_t = C_t^T Q_t^{-1} C_t + \overline{\Omega}_t$
5 $\quad \xi_t = C_t^T Q_t^{-1} z_t + \overline{\xi}_t$
} $\mathcal{O}(n^2)$

6 return ξ_t, Ω_t

6.1.5 Extended Information Filter (IF)

$$
\begin{aligned}
x_t &= g(u_t, x_{t-1}) + \varepsilon_t \\
z_t &= h(x_t) + \delta_t \\
G_t &= g'(u_t, \mu_{t-1}) \\
H_t &= h'(\mu_t)
\end{aligned}
$$

Extended Information Filter Algorithm: $(\xi_{t-1}, \Omega_{t-1}, u_t, z_t)$

2 $\quad \mu_{t-1} = \Omega_{t-1}^{-1} \xi_{t-1}$
3 $\quad \overline{\Omega}_t = (G_t \Omega_{t-1}^{-1} G_t^T + R_t)^{-1}$
4 $\quad \overline{\xi}_t = \overline{\Omega}_t \, g(u_t, \mu_{t-1})$
5 $\quad \overline{\mu}_t = g(u_t, \mu_{t-1})$
6 $\quad \Omega_t = \overline{\Omega}_t + H_t^T Q_t^{-1} H_t$
7 $\quad \xi_t = \overline{\xi}_t + H_t^T Q_t^{-1} \left[z_t - h(\overline{\mu}_t) - H_t \overline{\mu}_t \right]$

- ***Global uncertainty:*** set $\Omega = 0$ is better than set $|\Sigma| = \infty$
- IF tends to be numerically more stable than KF
- IF is better for multi-robot problems
- For high dimensional state, EKF is computational better than EIF

6.2 Measurements

6.2.1 Map Representation

Maps: $m = \{m_1, m_2, \ldots, m_N\}$
There are 2 ways to represent a map:

[TODO: Add images]

feature-based	location-based
m_n: properties of a feature and location of feature	a specific location
only the shape of the environment **at the specific locations**	volumetric: **label for any location** in the world
easy to adjust positions of objects ⇒ popular in the robotic mapping field	occupancy grid map

6.2.2 Measurement Noise

The 4 types of measurement noise:

- Correct range with local measurement noise
  With z_t^{k*} as the correct distance

$$p_{hit}(z_t^k|x_t, m) = \begin{cases} \eta\, \mathcal{N}(z_t^k|z_t^{k*}, \sigma_{hit}^2) & \text{if } 0 \leq z_t^k \leq z_{\max} \\ 0 & \text{otherwise} \end{cases} \tag{6.1}$$

- Unexpected object

$$p_{short}(z_t^k|x_t, m) = \begin{cases} \eta\lambda_{short} e^{-\lambda_{short} z_t^k} & \text{if } 0 \leq z_t^k \leq z_t^{k*} \\ 0 & \text{otherwise} \end{cases} \tag{6.2}$$

- Failures

$$p_{\max}(z_t^k|x_t, m) = I(z = z_{\max}) \tag{6.3}$$

- Random measurements

$$p_{rand}(z_t^k|x_t, m) = \begin{cases} \frac{1}{z_{\max}} & \text{if } 0 \leq z_t^k < z_{\max} \\ 0 & \text{otherwise} \end{cases} \tag{6.4}$$

[TODO: Add image, plot]

$$p(z_t^k|x_t, m) = \begin{bmatrix} z_{hit} \\ z_{short} \\ z_{max} \\ z_{rand} \end{bmatrix}^T \cdot \begin{bmatrix} p_{hit}(z_t^k|x_t, m) \\ p_{short}(z_t^k|x_t, m) \\ p_{max}(z_t^k|x_t, m) \\ p_{rand}(z_t^k|x_t, m) \end{bmatrix} \tag{6.5}$$

6.3 Robot Motion

Pose: $[x, y, \theta]^T$ at location $[x, y]^T$ and orientation θ

6.3.1 Motion Model

Motion Model, also known as (a.k.a.) Probabilistic Kinematic Model: $p(x_t, u_t, x_{t-1})$

Velocity commands	Odometry (distance traveled, angle turned, etc.)
	more accurate but post-the-fact (not for motion planning)
Use for Probabilistic motion planning	Use for estimation

Each has closed form calculation and sampling algorithm.

6.3.2 Velocity Motion Model

Assuming we can control a robot through velocities:

$$u_t = \begin{bmatrix} v_t \\ \omega_t \end{bmatrix}; \qquad x_{t-1} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix}; \qquad x_t = \begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix}$$

Motion Model Velocity Algorithm: (x_t, u_t, x_{t-1})

2 $\mu = \frac{1}{2}\frac{(x-x')\cos\theta + (y-y')\sin\theta}{(y-y')\cos\theta - (x-x')\sin\theta}$

3 $x^* = \frac{x+x'}{2} + \mu(y-y')$

4 $y^* = \frac{y+y'}{2} + \mu(x'-x)$

5 $r^* = \sqrt{(x-x^*)^2 + (y-y^*)^2}$

} Invert the motion model

6 $\Delta\theta = \text{atan2}(y'-y^*, x'-x^*) - \text{atan2}(y-y^*, x-x^*)$

7 $\hat{v} = \frac{\Delta\theta}{\Delta t} r^*$

8 $\hat{\omega} = \frac{\Delta\theta}{\Delta t}$

9 $\hat{\gamma} = \frac{\theta'-\theta}{\Delta t} - \hat{\omega}$

} compared actual velocities with the desired

10 return $p(v-\hat{v}, \alpha_1|v| + \alpha_2|\omega|) \cdot p(\omega-\hat{\omega}, \alpha_3|v| + \alpha_4|\omega|) \cdot p(\hat{\gamma}, \alpha_5|v| + \alpha_6|\omega|)$

Sample Motion Model Velocity Algorithm: (u_t, x_{t-1})

2 $\hat{v} = v + sample(\alpha_1|v| + \alpha_2|\omega|)$

3 $\hat{\omega} = \omega + sample(\alpha_3|v| + \alpha_4|\omega|)$

4 $\hat{\gamma} = sample(\alpha_5|v| + \alpha_6|\omega|)$

5 $x' = x - \frac{\hat{v}}{\hat{\omega}}\sin\theta + \frac{\hat{v}}{\hat{\omega}}\sin(\theta + \hat{\omega}\Delta t)$

6 $y' = y + \frac{\hat{v}}{\hat{\omega}}\cos\theta - \frac{\hat{v}}{\hat{\omega}}\cos(\theta + \hat{\omega}\Delta t)$

7 $\theta' = \theta + \hat{\omega}\Delta t + \hat{\gamma}\Delta t$

8 return $x_t = [x', y', \theta']^T$

- Probability normal distribution(a, b): return $\frac{1}{\sqrt{2\pi b}} e^{-\frac{a^2}{2b}}$
- Probability triangular distribution(a, b): return $\begin{cases} 0 & \text{if } |a| > \sqrt{6b} \\ \frac{\sqrt{6b} - |a|}{6b} & \text{else} \end{cases}$
- Sample normal distribution(b): return $\frac{b}{6}\sum_{i=1}^{12} rand(-1, 1)$
- Sample triangle distribution(b): return $b.rand(-1, 1).rand(-1, 1)$

6.3.3 Odometry Motion Model

Only available after the robot has moved
⇒ only use for filter algorithm
not for accurate motion planning and control

Motion Model Odometry Algorithm: (x_t, u_t, x_{t-1})

2 $\delta_{rot1} = \text{atan2}(\bar{y}' - \bar{y}, \bar{x}' - \bar{x}) - \bar{\theta}$

3 $\delta_{trans} = \sqrt{(\bar{x} - \bar{x}')^2 + (\bar{y} - \bar{y}')^2}$

4 $\delta_{rot2} = \bar{\theta}' - \bar{\theta} - \delta_{rot1}$

5 $\hat{\delta}_{rot1} = \text{atan2}(y' - y, x' - x) - \theta$

6 $\hat{\delta}_{trans} = \sqrt{(x - x')^2 + (y - y')^2}$

7 $\hat{\delta}_{rot2} = \theta' - \theta - \hat{\delta}_{rot1}$

} ⇒ inverse motion model

8 $p_1 = prob(\delta_{rot1} - \hat{\delta}_{rot1}, \alpha_1\hat{\delta}_{rot1} + \alpha_2\hat{\delta}_{trans})$

9 $p_2 = prob(\delta_{trans} - \hat{\delta}_{trans}, \alpha_3\hat{\delta}_{trans} + \alpha_4(\hat{\delta}_{rot1} + \hat{\delta}_{rot2}))$

10 $p_3 = prob(\delta_{rot2} - \hat{\delta}_{rot2}, \alpha_1\hat{\delta}_{rot2} + \alpha_2\hat{\delta}_{trans})$

11 return $p_1.p_2.p_3$ $(= p(x_t|u_t, x_{t-1}))$

NOTE:

- Bar $\Leftrightarrow$ measurements

$$\overline{x}_{t-1} = [\bar{x} \quad \bar{y} \quad \bar{\theta}]^T$$
$$\overline{x}_t = [\bar{x}' \quad \bar{y}' \quad \bar{\theta}']^T$$

- Hat $\Leftrightarrow$ estimations
- No bar and hat $\Leftrightarrow$ hypothesized final pose x, y

Sample Motion Model Odometry Algorithm: (u_t, x_{t-1})

2 $\quad \delta_{rot1} = \text{atan2}(\bar{y}' - \bar{y}, \bar{x}' - \bar{x}) - \bar{\theta}$

3 $\quad \delta_{trans} = \sqrt{(\bar{x} - \bar{x}')^2 + (\bar{y} - \bar{y}')^2}$

4 $\quad \delta_{rot2} = \bar{\theta}' - \bar{\theta} - \delta_{rot1}$

5 $\quad \hat{\delta}_{rot1} = \delta_{rot1} - sample(\alpha_1\delta_{rot1} + \alpha_2\delta_{trans})$

6 $\quad \hat{\delta}_{trans} = \delta_{trans} - sample(\alpha_3\delta_{trans} + \alpha_4(\delta_{rot1} + \delta_{rot2}))$

7 $\quad \hat{\delta}_{rot2} = \delta_{rot2} - sample(\alpha_1\delta_{rot2} + \alpha_2\delta_{trans})$

8 $\quad x' = x + \hat{\delta}_{trans}\cos(\theta + \hat{\delta}_{rot1})$

9 $\quad y' = y + \hat{\delta}_{trans}\sin(\theta + \hat{\delta}_{rot1})$

10 $\quad \theta' = \theta + \hat{\delta}_{rot1} + \hat{\delta}_{rot2}$

11 $\quad$ return $\quad x_t = [x' \quad y' \quad \theta']^T$

6.3.4 Map-based Motion Model

Map-based Motion Model: $p(x_t|u_t, x_{t-1}, m)$

- Occupancy maps: $p(x_t|m) = 0 \Leftrightarrow$ the robot collides
- If the distance from $x_{t-1} \rightarrow x_t$ is small enough ($<$ half the robot's diameter), we can estimate the probability (prob.) $p(x_t|u_t, x_{t-1}, m) \approx \eta p(x_t|u_t, x_{t-1})p(x_t|m)$, which discards the info relating the robot's path to x_t

Motion Model with Map Algorithm: (x_t, u_t, x_{t-1}, m)

return $p(x_t|u_t, x_{t-1}).p(x_t|m)$

Sample Motion Model with Map Algorithm: (u_t, x_{t-1}, m)

$do:$

$x_t = sample\_motion\_model(u_t, x_{t-1})$

$\pi = p(x_t|m)$

$until \quad \pi > 0$

$return < x_t, \pi >$

7 GNN in Robotics

For introduction to Graph Neural Network (GNN), check Sec. GNN (AI notes.pdf)

Graph data structure are helpful in some of the following robotics problems:

- Multi-robot: nodes are robots (most of current work 2022).
  There are research on path planning, exploration problems.
- Multi-object interactions: nodes are objects, the robot itself Lin et al. (2022) [LWU+22]. *"Efficient and interpretable robot manipulation with graph neural networks"*.

This field is still quite new (2022)

8 Sim-to-Real Transfer

8.1 Introduction

Check *"Perspectives on Sim2Real transfer for robotics: A summary of the Robotics: Science and System 2020 workshop"* [HBH+20] to understand current limitations, directions, open questions, etc.

For more application examples / experiments, check this *mehhhhh* review: *"Sim-to-Real Transfer in Deep Reinforcement Learning for Robotics: A Survey"* [ZQW20]

8.2 Zero-shot Transfer

- Build a realistic simulator, or to have enough simulated experience
- Apply the model directly in real-world settings

8.3 Domain Randomization

Domain randomization is the approach to vary the simulation settings, in hope that the model learns to generalize to real-world setting. In some sense, each roll-out is simply a sample from a certain distribution of simulation params..

- Can be divided into two kinds: *visual randomization* and *dynamics randomization*
- Tobin et al. (2017) [TFR+17] randomizes settings for pickup task
  - Objects: number, shape, position and texture
  - Camera: position, orientation, and field of view
    - Position: random within a small fixed box ($10 \times 5 \times 10cm$) around initial point.
    - The camera viewing angle: is offset by up to $0.1rad$ from a fixed direction.
    - The field of view is scaled by up to 5% from the starting point.
  - Lighting conditions: number, position, orientation, and specular characteristics.
- Sadeghi et al. (2016) [SL16] randomize furniture, texture for drone's path planning problem.

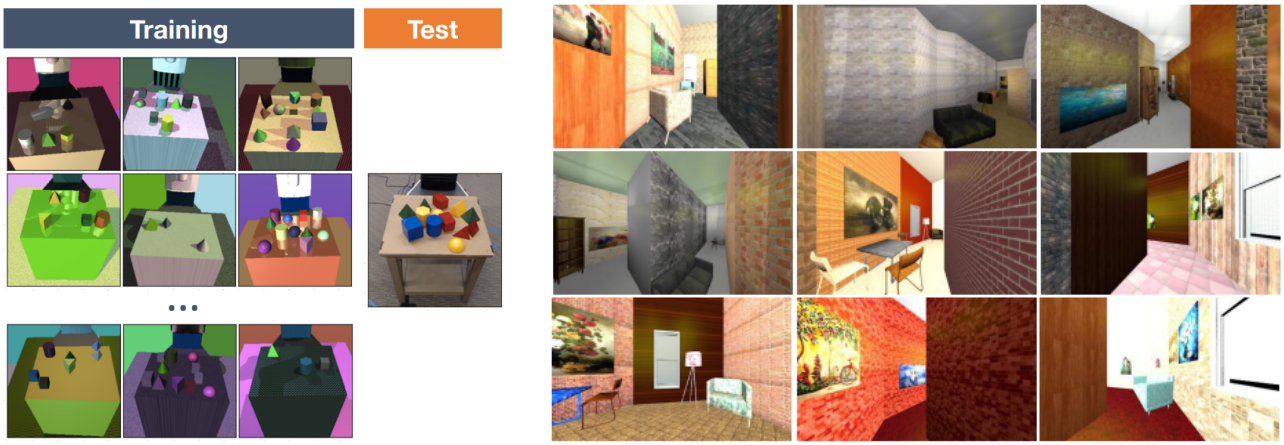


Figure 8.1: Illustration of domain randomization [SL16; TFR+17].

8.4 Adapting Simulation Randomization

Domain randomization requires significant expertise and manual fine-tuning to design the distribution $p(\xi)$ for simulation params.. In addition, overly wide distributions can hinder successful policy learning. The SimOpt approach adaptively optimize simulation params. with real-world experience. [CHM+19]

8.5 Domain Adaptation

Domain Adaptation is the process that allow an Artificial Intelligence (AI) system trained in source domain to generalize to a target domain. In robotics, the source domain is the simulation and the target domain is the real world.

- Labeled data is easily available from simulation / source domain
- Unlabeled data from real world / target domain can usually be collected, but labels are more difficult to obtain.
  - ***Unsupervised*** domain adaptation: **no labels** in the target domain
  - ***Semi-supervised*** domain adaptation: **fewer labels** in the target domain than in source domain
- *Pixel-level domain adaptation*: re-stylize images from the source domain to make them look like images from the target domain
  NOTE: This is basically is neural style transfer in Computer Vision (CV) with Generative Adversarial Network (GAN)s
  Examples:
  - SimGAN has GAN and similarity loss [SPT+17]
  - PixelDA adds task loss to the two above [BSD+17]

- *Feature-level domain adaptation*: focuses on learning domain-invariant features
  - A mapping of fixed, pre-computed features between source and target domains [SFS16]
  - DANN: A domain-invariant feature extractor with similarity loss (preferred method, using Convolutional Neural Network (CNN)) [GUA+16]

Example:

- Applying both pixel-level and feature-level domain adaptation: Bousmalis et al. (2018) [BIW+18]. *"Using simulation and domain adaptation to improve efficiency of deep robotic grasping"*.

8.6 Knowledge Distillation

Policy distillation is the process of extracting knowledge from a teacher network to a significantly smaller and more efficient student network, while maintaining a similarly expert level. The student is trained in a supervised manner with data generated by the teacher network.

[**TODO: DisCoRL, a modular, effective and scalable pipeline for continual learning**]

8.7 References

- Overview:
  - Höfer et al. (2020) [HBH+20]. *"Perspectives on Sim2Real transfer for robotics: A summary of the Robotics: Science and System 2020 workshop"*.
  - Zhao et al. (2020) [ZQW20]. *"Sim-to-Real Transfer in Deep Reinforcement Learning for Robotics: A Survey"*.
  - Karol Arndt, Murtaza Hazara, Ali Ghadirzadeh, and Ville Kyrki. Meta reinforcement learning for sim-to-real domain adaptation. arXiv:1909.12906, 2019.
  - Continual reinforcement learning deployed in real-life using policy distillation and sim2real transfer
- Domain randomization:
  - Chebotar et al. (2019) [CHM+19]. *"Closing the Sim-to-Real Loop: Adapting Simulation Randomization with Real World Experience"*.
  - Tobin et al. (2017) [TFR+17]. *"Domain randomization for transferring deep neural networks from simulation to the real world"*.
- Domain adaptation:
  - Pixel-level domain adaptation:
    - Shrivastava et al. (2017) [SPT+17]. *"Learning from Simulated and Unsupervised Images Through Adversarial Training"*.

    - Bousmalis et al. (2017) [BSD+17]. *"Unsupervised Pixel-level Domain Adaptation with Generative Adversarial Networks"*.
  - Feature-level domain adaptation: Ganin et al. (2016) [GUA+16]. *"Domain-adversarial training of neural networks"*.
  - Both: Bousmalis et al. (2018) [BIW+18]. *"Using simulation and domain adaptation to improve efficiency of deep robotic grasping"*.
- Knowledge distillation

9 Natural Planning Model

Structure is everywhere. An essay has a structure including the introduction, main body and conclusion. A house has a structure including the foundations, walls, roof. All living bodies, complex entities, organizations have structure. Within a structure, every part has its own responsibilities and connections with other parts. The clearer an entity is structured, the more functional and easier it is to improve. A body builder who wants to increase the size of his chest will go bench press, not squat. A company which wants to improve its branding will spend more investment on marketing, not logistics. As a roboticist, I asked myself: have robots follow a structured planning process (the answer is less or more). But the more challenging question is how could we bring more structure to robot planning?

As always, it is beneficial to look at the robot's closest friend, the human kind. The rephrased questions would be: (1) do we think in structure? (2) is thinking with structure better than without it? (3) could we bring more structure to our thinking? For the first two questions, the answer is rather uncertain, as we are humans, but generally it is a "YES". E.g., a good chess player will consider various aspects in a structured manner: hanging pieces, board space, king's safety, etc. Experienced Sudoku solver will strategically scan over each number, each line, each row, each block. This also makes sense from the point of biology, specifically neuroscience. Our brains and the animals' brains are hierarchically structured. The animal's brain is structured into the forebrain, midbrain, hindbrain and spinal cord, in which the closer to the spinal cord, the more basic the functionalities a part is responsible for. Our brain is structured into the cerebrum, thalamus, brainstem and cerebellum. Studies have shown that there is clear difference in task complexity which each part is responsible for. E.g.: the cerebrum is responsible for high-level thinking, information processing (personality, decision-making, emotion, senses, language, etc.), while the cerebellum or brainstem are responsible for more basic muscle control and involuntary body functions (muscle memory, breathing, circulation, digestion, etc.)

The last and only question left is how to bring more structure into human thinking and robot planning? Whenever I come across ideas or approaches in other fields, I always try to find out whether there is possible connection or adaptation to robotics. I came upon this idea of the *Natural Planning Model* which has various correspondences in robotics. The Natural Planning Model hypothesizes that the human brain tends to follow a five-step procedure before carrying on a sequence of complex actions [All02].

1. Defining Purpose and Principles

2. Outcome Visioning
3. Brainstorming
4. Organizing
5. Identifying Next Actions

I would argue that we would manage to fit most of conducted robotic experiments in this 5-stage planning framework. That is because experiments are designed by humans, and that we unconsciously follow this natural planning model. Thus, the planning model is imprinted in their programs and the design of their experiments. The following parts cover the above steps and their corresponding robotic frameworks. I wish this framework to be the skeleton for other tools and modules, like the muscles, to attach to. If there are any current limitations (reaction time, accuracy, etc.), they should be limitations that can be tackled by improving other modules.

9.1 Robot Planning

Let's first have a definition of what does robot planning even mean. [McD92; SKK08]

- Robot planning is the ***automatic generation, debugging, or optimization*** of robot plans (or robot programs), by reasoning **explicitly** about the consequences of alternative plans.
- The plan needs not to be executed in its entirety. It should be the high-level plan, not low-level physical control. In addition, there can be changes that the plan needs to adapt, e.g. chess.
- Purposes of a plan:
  - keeps a certain state true,
  - devise the most efficient plan for a certain task,
  - react to a type of recurring world state,
  - or some combination of all these things.
- Ideally... the robot executes the plan while the planner thinks about improving it...

9.2 Purpose and Principles

Purposes are the great answers to the "WHY" questions. We eat and drink to survive. We go to college in search for knowledge and skills. We travel and go out with our friends to relax and enjoy our lives. Well, for know, the simple yet sufficient "WHY" for robots is the fact that we, humans, are lazy and want our lives to be more comfortable :)

Principles are stated as the values that we hold for ourselves. These values create boundaries between the actions that are acceptable and those which are not. E.g., those who treasure honesty would not lie to gain benefit. In similar manner, robots' principles would be the constraints that they have to operate under. If it's necessary, they will override lower-level commands. With that notion in mind, some of the basic constraints are:

- Asimov's three law of robotics [Asi04]
  - First Law: A robot may not injure a human being or, through inaction, allow a human being to come to harm.
  - Second Law: A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
  - Third Law: A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.
- Other safety and physical constraints, in terms of force, torque, velocity, acceleration
- Task-related constraints: e.g., in chess, there are rules about how a piece moves

9.3 Outcome Visioning

Knowing the answer to the "WHY" question, we start envision the desired outcomes, the answers for the "WHAT" questions. A chef imagines what food is on the final plate, how they taste, look and smell like. An architect imagines what rooms, functionalities a house has, how each room looks like, how the light, air, water travel in the house.

Some robotic works have followed this line of thought:

- Goal-conditioned learning
  - [**TODO: cite goal-proposed RL exploration mechanism**]
  - Andrychowicz et al. (2017) [AWR+17]. *"Hindsight Experience Replay"*.
- Contextual learning [**TODO:**]
- Multi-model goal "imagination"
  - Sharma et al. (2019) [SPG19]. *"Third-person Visual Imitation Learning via Decoupled Hierarchical Controller"*. (badly written, but still)
  - [**TODO:**]

9.4 Brain Storming and Organizing

Brain Storming and Organizing are two separate steps. Brainstorming is the step in which we start breaking down the desired goal in an unstructured way. We list out related entities

(relevant subtasks, objects, people) in an unordered manner. For example, with the goal to have a dinner with friends, following problems could arise in one's mind in unordered sequence: are our friends available, where would we eat, what time will we meet, do they have specific allergies. Then, organizing is the step when we start putting these subtasks, other entities into relations and sequence based on prioritization. For the prior example, we start with creating a group chat to discuss (check availability, date and time), then we call the restaurant (check availability, book table).

Existing robotic frameworks can be divided into two problems:

- Interpreting the interaction, relation with other entities (objects, agents)
- Breaking down a complex task into sequence of simple known tasks

9.4.1 Interaction Planning

- Interaction with other objects using a graph, in which the nodes are objects and the robot itself
  - Lin et al. (2022) [LWU+22]. *"Efficient and interpretable robot manipulation with graph neural networks"*.
  - Sieb et al. (2020) [SXH+20]. *"Graph-structured Visual Imitation"*.
- Relation with other agents / robots
  - Zhang et al. (2019) [ZN19]. *"Robot learning and execution of collaborative manipulation plans from YouTube cooking videos"*.

9.4.2 Breaking Down the Plan

- Explicit planning by human
  - Smith et al. (2019) [SDZ+19]. *"AVID: Learning Multi-Stage Tasks via Pixel-Level Translation of Human Videos"*.
  - Brooks (1982) [Bro82]. *"Symbolic error analysis and robot planning"*.
- Learning and formalizing a plan with symbolic representation and action grammar.
  - Zhang et al. (2019) [ZN19]. *"Robot learning and execution of collaborative manipulation plans from YouTube cooking videos"*.
  - Toussaint et al. (2018) [TAS+18]. *"Differentiable Physics and Stable Modes for Tool-Use and Manipulation Planning"*.
  - Yang et al. (2015) [YLF+15]. *"Robot Learning Manipulation Action Plans by Watching" Unconstrained Videos from the World Wide Web"*.

Sometimes, there are many possible plans to reach a goal. Then plan could be chosen based on addition constraints or rules for optimization / selection. E.g., to cook a dish with a piece of steak, potatoes and veges, one could vary on the ingredient to start with, and switch to work on the others any time. The time duration to finish cooking, the quality of the food could be included as additional constraints to cancel out redundant plans.

9.5 Identifying and Taking Action

A library of primitive actions plays a great role. A primitive action should be meaningful, but also general enough to be efficient. Some works focus on motor control (force and torque) that leads to jiggering motion artifacts. We don't want the arm to move around like that. We want a smooth and decisive movement, but of course, can still subject to minor error and stochasticity.

Generality implies that if we want to go to 1 from 0, we don't want to step by step specify it to go to 0.1, 0.2, etc. What we want is for it to go to the neighbor of 1 in one single movement.

- Motor primitives [**TODO: sth**]
- [**TODO:**]

Goal-based policy learning

-

9.6 References

[**TODO:**]

- Robot planning
  - **NOTE:** A great but long and complex paper: McDermott (1992) [McD92]. *"Robot Planning"*.
  - Brooks (1982) [Bro82]. *"Symbolic error analysis and robot planning"*.
- Goal imagining mechanism: wide range of works
- Goal-conditioned learning:
- Learning action plan
- Primitive motion

10 Research Proposal

10.1 Introduction and Background of Interest

[**TODO: ignore for now**]

Robots are complex machines designed to support our lives.

Since mid 19th century, its emergence has received research attention in both the academic and industry. The first major application was in the automotive industry. Its presence is entering our lives in different fields is spreading even more and more. [**TODO: move to unstructured environments and challenges**]

10.2 Literature Review

To my best current knowledge, robot arms have made significant improvement, but are still far from delivering general-purpose tasks. Initially, robot arms are programmed explicitly and only capable of working in the known and constrained environment of factories. Progress in different fields of technology has provided the robots more inputs (e.g., vision, audio, haptic) to operate in dynamic and unstructured environments. State-of-the-art robot manipulators can deliver complex tasks, e.g., cooking [Mol], making coffee [Cof], and cleaning around the house [Bot]. However, the behaviors of these models are still awkwardly disruptive and far from the mastery level of the human hand's dexterity. In addition, instead of having the adaptability for a wide range of conditions, most models still operate in designed environments with known tools and settings.

10.2.1 Robotic Grasping

Grasping is one of the critical and unavoidable problems for robot manipulators, especially for logistic and service robots. Overall, most successful grasping approaches are empirical, using deep learning on a large dataset to find the best grasping candidates. Majority of models are supervised learning using single-modal input, i.e. RGB images. A few have considered multi-modal inputs: RGB with depth images or tactile input. Approaches, which take tactile data, use it as the sole input to improve grasp stability, adaptability to object's weight [BLJ+11; LBK+14], a few combine with other modality for improvement [COU+17]. [BMA+13; CRC18; LLC+19; KBK+20]

10.2.2 Reinforcement Learning

Reinforcement Learning (RL) is a branch of Machine Learning (ML) approaches for learning decision making from experiences. Given a sufficient amount of input data, it can potentially surpass human's ability for reasoning, e.g., playing games like Go, chess, Atari. Most works on robot manipulators are currently directed to object picking and hand-over tasks. To meet the need for data, sim-to-real transfer techniques [KBK+20] and collective learning are being studied [YLK+17]. Unlike in other domains of ML, it's difficult to implement transfer learning with RL, given different robot arms, gripper and sensor types. Various directions are being researched to tackle this issue, i.e. offline RL, novel exploration strategies, multi-task learning, meta-learning. [KBP13; Li17; ADB+17; SKS21]

10.3 Approaches and Choice of Methods

10.3.1 Key Points for Improvement

Prior works on robotic manipulators were limited on their utilization of tactile sensors. Because complex hand and arm behaviors need force and pressure feedback, leveraging the manipulators to the dexterity level of human's arms requires these sensors. However, tactile sensors are currently been used mostly for the development of soft robotics [HJL18]. For grasping tasks, despite certain successes from using visual and tactile input separately, there hasn't being a multi-modal approach capable of combining the strengths of both sides, i.e., accurate localization, adaptability to object properties. A model, which has knowledge from both visual and tactile sources, promises to deliver complex manipulation tasks with diverse objects.

It's still challenging to generalize and apply RL to different robotic manipulator's tasks. In general, RL did make a convincing case about its potential to surpass human's ability in some specific applications, e.g., playing Go, chess. However, in other fields, practical applications are yet scattered and limited. For robotic manipulators, current focuses are still around object picking and handling tasks [SKS21]. One of the major causes for this situation is the current gap in generalization and transfer learning. Directions for improvements are meta-learning, multi-task learning, etc. [KBP13].

Robot manipulation [BK19]

10.3.2 Approaches and Research Contributions

The progress I wish to work towards concerns robotic collective learning for collaborative tasks. For example, a system of multiple robot arms learning to play 2v2 table tennis, pack an item or cook. Building up towards this progress, I intend to work and gain more experiences on the following problems:

1. A multi-modal approach for robotic picking task: combines visual and tactile input into a Deep Learning (DL) model. Prior works on tactile sensors have proven their potentials in inference of object properties [LBD+17] and improving robotic grasping [YA19]. I want to further extend recent advances in tactile sensors to a multi-modal approach.
2. Visual imitation learning: copies behaviors from visual demonstrations (videos). Prior works are still restricted with certain types of input data, tasks [FYZ+17; SPG19]. Based on previous progress on teleoperation [HVWY+20], I want to extend further to learn in different problem settings, with generalized tasks, and also apply offline RL.
3. A data collection pipeline for robot manipulators: preferably from using the above visual imitation learning, to map human's arm movements to manipulator's. The data would contain both visual and tactile information. It would then be used for the learning of other robotic tasks or in other settings (different types of arm, gripper, etc.).
4. Meta-learning with different manipulation tasks.

Moreover, I'm also interested in exploring the usage of certain DL models, techniques:

- Generative model: Generating expert-like samples.
- Score matching
- Exploration for imitation learning

10.4 Proposed Research Plan

[TODO:]

[TODO: How the lab is related to this research plan?]

- There is alignment in our directions
- Fit the position

[TODO: Give compliments to their works!]

- mention more explicitly regarding the topics, what research they have done
- I read your papers about ... let alone the works on ...

11 Technical Tools

This chapter talks about or at least lists out helpful tools, platforms for using/working with robotics.

11.1 MuJoCo

MuJoCoPy Lec 2a: 2D Manipulator modeling (Part 1 of 2)

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