Combining Optimal Control and Learning for Visual Navigation in Novel Environments

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Introduction

MLRG Summer 2020: Optimal Control

- So far...
  - Fundamentals - Engineering Perpsective (Cathy)
  - Fundamentals - Optimization Perspective (Ben)
  - Iterative LQR and Guided Policy Search (Betty)
  - Sample Complexity of LQR (Joey)
  - Model Predictive Control and Safe RL (Fred)

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- Today...
  - Robots 😎

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- Factorized approach: learning is used to make high level navigational decisions, optimal control used to produce smooth trajectories

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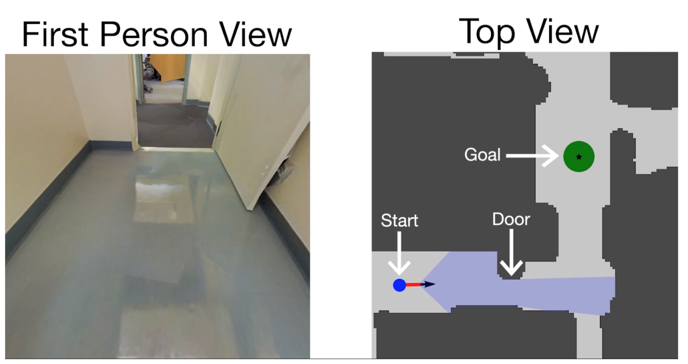
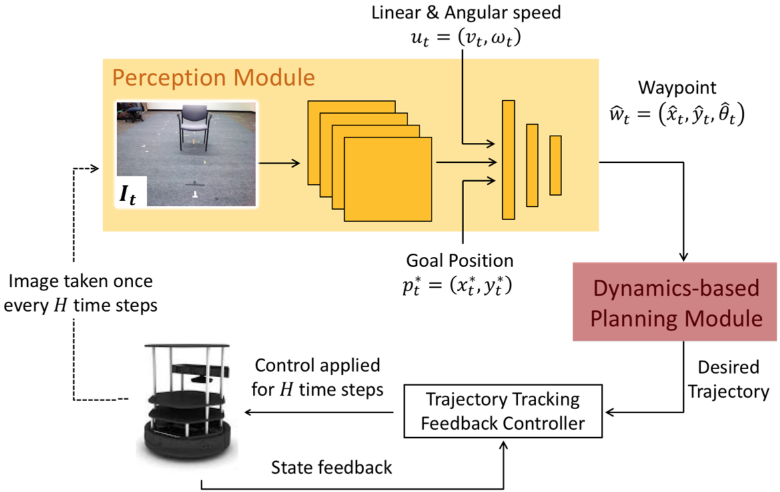


Approach

System Diagram



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- Notation and Terminology:
    - State: $z_t = (x_t, y_t, \phi_t)$

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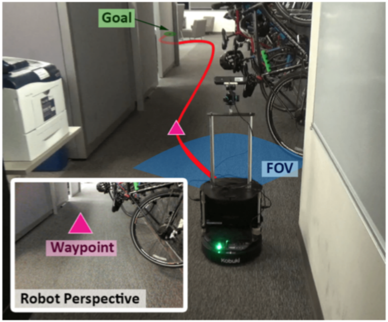
  - $v \in [0, \bar{v}], \quad \omega \in [-\bar{\omega}, \bar{\omega}]$

Perception Module

A CNN which takes as input

- A 224×224 pixel RGB image
- The target position p_t^*
- The robots current linear and angular speed u_t

and outputs a waypoint $\hat{w}_t := (\hat{x}_t, \hat{y}_t, \hat{\phi}_t) = \psi(I_t, u_t, p_t^*)$



Planning and Control Module

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$$\{z^*, u^*\}_{t:t+H} = \mathit{FitSpline}(\hat{w}_t, u_t).$$

- An LQR-based feedback controller

$$\{k, K\}_{t:t+H} = \mathit{LQR}(z^*_{t:t+H}, u^*_{t:t+H})$$

tracks the generated trajectory.

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- Output is a sequence of dynamically feasible waypoints and corresponding spline trajectories.
- Optimal trajectories can be found in the training phase as this process is done in simulation with perfect knowledge of the environment.

Cost Function

Cost function for trajectory is

$$J(\mathbf{z}, \mathbf{u}) = \sum_{i=0}^{T} J_i \left(z_i, u_i\right)$$

where

$$J_i \left(z_i, u_i\right) := \left(\max \left\{0, \lambda_1 - d^{obs} \left(x_i, y_i\right)\right\}\right)^3 + \lambda_2 \left(d^{goal}(x_i, y_i)\right)^2$$

and

- $d^{obs} \left(x_i, y_i\right)$ is the distance to the nearest obstacle at time i
- $d^{goal}(x_i, y_i))$ is the minimum collision-free distance to the goal position
- λ_1 is the minimum allowable distance to an obstacle

MPC Problem

Given the cost function in the last slide, the MPC problem is

$$\min_{\mathbf{z},\mathbf{u}} J(\mathbf{z},\mathbf{u})$$

subject to constraints

$$x_{i+1} = x_i + \Delta T v_i \cos\phi_i, \quad y_{i+1} = y_i + \Delta T v_i \sin\phi_i, \quad \phi_{i+1} = \phi_i + \Delta T \omega_i$$

$$v_i \in [0, \bar{v}], \quad \omega_i \in [-\bar{\omega}, \bar{\omega}]$$

$$z_0 = (0,0,0), \quad u_0 = (0,0)$$

MPC Problem

Starting from $i = 0$, we solve the optimization problem on the last slide in a receding horizon fashion. That is, for a timestep $i = t$ we solve

$$\min_{\hat{w}_t} \sum_{i=t}^{t+H} J_i\left(z_i, u_i\right)$$

subject to

$$\{z, u\}_{t:t+H} = \text{FitSpline}\left(\hat{w}_t, u_t\right),$$

$$z_t, u_t - \text{ Given}$$

where

- $\hat{w}_t = (\hat{x}_t, \hat{y}_t, \hat{\phi}_t)$ is the waypoint
- $\{z, u\}_{t:t+H}$ is the corresponding trajectory

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- Choose lowest cost sample $\hat{w}^*_t$
- Repeat starting from time $t + H$

Training Data for Perception Module

The solution to each instance of this optimization problem gives a training example comprised of:

- The image obtained at state z_t^*, I_t
- The relative goal position p_t^*
- The speed of the robot, u_t^*
- The optimal waypoint $\hat{w}_t^*$

Algorithm

Algorithm 1 Model-based Navigation via Learned Waypoint Prediction

Require: $p^* := (x^*, y^*)$ ▷ Goal location

for $t = 0$ to T **do**
- $z_t := (x_t, y_t, \phi_t);\quad u_t := (v_t, \omega_t)$ ▷ Measured robot pose, and linear and angular speed
- **Every** H steps **do** ▷ Replan every H steps
  - $p_t^* := (x_t^*, y_t^*)$ ▷ Goal location in the robot's coordinate frame
  - $\hat{w}_t = \psi(I_t, u_t, p_t^*)$ ▷ Predict next waypoint
  - $\{z^*, u^*\}_{t:t+H} = FitSpline(\hat{w}_t, u_t)$ ▷ Plan spline-based smooth trajectory
  - $\{k, K\}_{t:t+H} = LQR(z^*_{t:t+H}, u^*_{t:t+H})$ ▷ Tracking controller
- $u_{t+1} = K_t(z_t - z_t^*) + k_t$ ▷ Apply control

end for

Experiments

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  - Memory vs. Memoryless
  - Uses the same spline-based planner

Simulation - Setup

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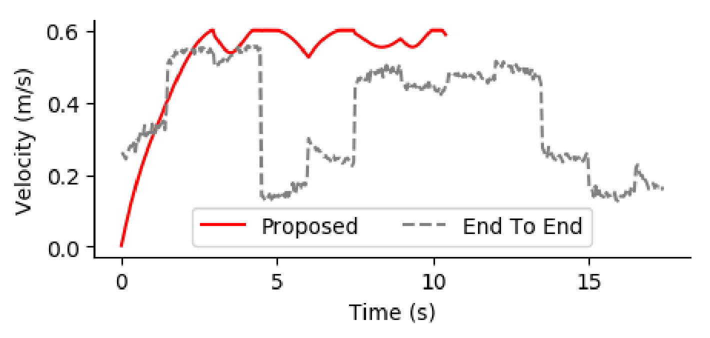
- 185 test episodes from a third, held-out building used for testing
- Test episodes sampled to include scenarios such as: avoiding obstacles, leaving/entering rooms, using hallways, etc.
- Metrics: success rate, average time to reach goal, average acceleration and jerk

Simulation - Quantitative Results

Agent	Input	Success (%)	Time taken (s)	Acceleration (m/s^2)	Jerk (m/s^3)
Expert	Full map	100	10.78 ±2.64	0.11 ±0.03	0.36 ±0.14
LB-WayPtNav (our)	RGB	80.65	11.52 ±3.00	0.10 ±0.04	0.39 ±0.16
End To End	RGB	58.06	19.16 ±10.45	0.23 ±0.02	8.07 ±0.94
Mapping (memoryless)	Depth	86.56	10.96 ±2.74	0.11 ±0.03	0.36 ±0.14
Mapping	Depth + Spatial Memory	97.85	10.95 ±2.75	0.11 ±0.03	0.36 ±0.14

Simulation - Qualitative Results



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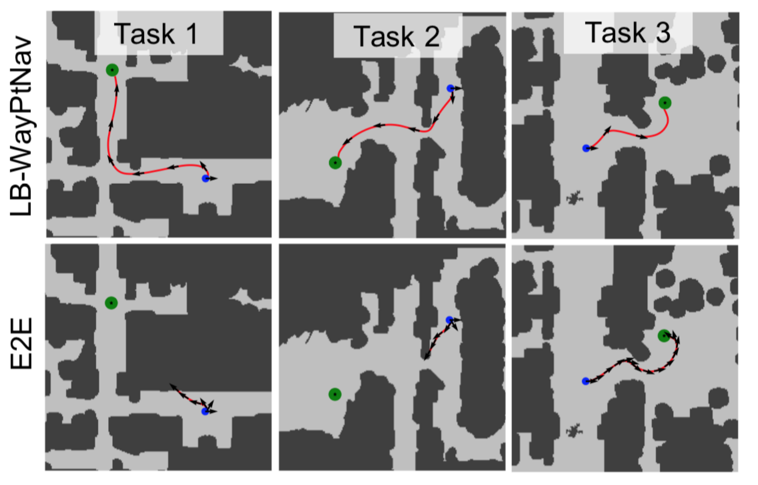

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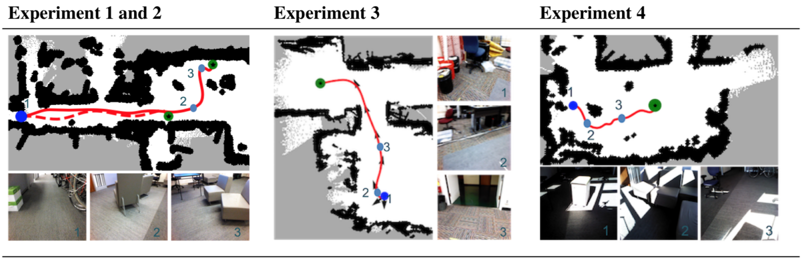
- On-board odometry is used for state measurement.
- 4 different experiments, each repeated 5 times for each method.

Hardware - Experiments



Hardware - Example

Video

Hardware - Quantitative Results

Agent	Input	Success (%)	Time taken (s)	Acceleration (m/s^2)	Jerk (m/s^3)
LB-WayPtNav (our)	RGB	95	22.93 ±2.38	0.09 ±0.01	3.01 ±0.38
End To End	RGB	50	33.88 ±3.01	0.19 ±0.01	6.12 ±0.18
Mapping (memoryless)	RGB-D	0	N/A	N/A	N/A
Mapping	RGB-D + Spatial Memory	40	22.13 ±0.54	0.11 ±0.01	3.44 ±0.21

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- More reliable and efficient at reaching goals than comparable methods
- Can be directly transferred from simulation to hardware in previously unseen environments

Dynamic Environments

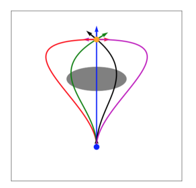
Video

Questions/Discussion

Appendix

Splines

The choice of $\hat{\phi}$ in $\hat{w}$ provides an additional degree of freedom, allowing the robot to select collision free trajectories.



Training vs. Test Areas

(a) Training

(b) Test

Data Augmentation

(a) Undistorted image

(b) Adding superpixels

(c) Adding Gaussian blur

(d) Adding motion blur

(e) Image sharpening

(f) Adding Gaussian noise

(g) Changing brightness

(h) Dropping pixels

(i) Changing saturation

(j) Changing contrast

(k) Changing field-of-view

(l) Changing camera tilt