coggle
made for free at coggle.it

Perceptive Systems

Visual Servoing
Traditional Solution

Set of target locations in the form of reference images 1-[30]

Difference between reference and current image must be small - Problems

- Motion Blur
- High Speed
- Occlusions

Gate Detectors
Traditional hand crafted

Problems

- Occlusions (=Partial Visibility)
- Motion Blur

Vision Based Systems

Hybrid ML System
perceptual awareness of a [CNN] with speed and accuracy of a state-of-the-art trajectory generation and tracking pipeline

Experiments

Simulation

Output

- Higher Robustness and Precision than state-of-the-art, highly engineered systems
- Compactness for Onboard Execution
- Highly Dynamic Environments
- Severe Occlusions (=Partial Visibility)
- Complex Navigation Tasks (seeking moving gates, racing though tracks)

Real World

Jointly Training

Training Imitation Learning

Supervision

Requirements at Training Time

- Location of Gates in Reference Frame
- Accurate State Estimates of Quadrocopter in Reference Frame

Pre-computed Global Trajectory $\mathbf{t}_g$
Minimum Snap 1-[19]

Variety of race track layouts

Variant of DAgger 1-[26]

Simulation

Recovering when learned policy deviates far from the reference trajectory

Data Collection

- State Estimates
- Corresponding Camera Images

Dataset

Ground Truth with Expert Policy

Manually Carrying the quadrotor through the track
Sufficient Coverage of Off-Trajectory Positions

Real World

Expert Policy

Project $\hat{\mathbf{p}}_g$ onto image plane
→ Ground Truth Normalized Image Coordinates $\hat{\mathbf{z}}_g$

Normalize Speed at $\hat{\mathbf{p}}'_g$ with maximum speed along $\mathbf{t}_g$
→ Desired Speed $\hat{\mathbf{v}}_g$

distance($\hat{\mathbf{p}}_c, \hat{\mathbf{p}}_g$) < Prediction Horizon $\mathbf{d} \in \mathbb{R}$
→ Desired Position $\hat{\mathbf{p}}_g$

Closest Point on $\mathbf{t}_g$
$\hat{\mathbf{p}}'_g$

Quadrotor Position
$\hat{\mathbf{p}}_c \in \mathbb{R}^3$

Network is not directly imitating the demonstrated behavior. Thus, performancecabilities of learned policy are not upper-bounded by performancecabilities of provided demonstrations

Shown with Cross Validation
Optimal weight: $\gamma = 0.1$
but performance mostly insensitive to weight

Loss Function - Weighted MSE loss on point and velocity predictions
$L = \|\hat{s} - \hat{s}_g\|^2 + \gamma \|\dot{s} - \dot{s}_g\|^2$

Reshid-based architecture of Loquercio et al. [17]
- efficient for onboard

Design

10 Frames per Second

Performance

Perception with CNN

Generalization to Dynamic Environments
Increased Robustness

ONLY Raw image from facing-forward onboard camera
in the paper: 300x200 RGB image

Input

Learned Policy

Able to reason on high-dimensional raw sensory input

Output

Waypoint in Local Image Coordinates
$\hat{\mathbf{z}} \in [-1, 1]^2$

Normalized Desired Speed
$v \in [0, 1]$

Subsystems

Path-Planning

Input

Conversion of $\hat{\mathbf{z}}$ to 3D local frame coordinates
$\hat{\mathbf{p}}_g = [\hat{p}_{gx}\ \hat{p}_{gy}\ \hat{p}_{gz}\ 1_m]$

Transfer Procedure

Minimum Jerk Trajectory Segment $\mathbf{t}_g$
1-[20]

Output

Input

Low-Level Control

Track $\mathbf{t}_g$ with control scheme by Faessler et. al. 1-[15]

Motor Commands
Low-Level Control Commands

Output

Minimum Jerk Trajectory 1-[20]
computationally efficient

Conversion of $\mathbf{v}$ to desired quadrotor speed $\mathbf{v}_{des}$
$\mathbf{v}_{des} = v_{max} \cdot \mathbf{v}$
v_{max} user-defined, controls aggressiveness of flight

Set prediction horizon $\mathbf{d}$ proportional to $\mathbf{v}$
Set depth: $\hat{\mathbf{p}}_{gz} = \mathbf{d}$

Back-project $\hat{\mathbf{z}}$ *along camera projection ray*
→ $\hat{\mathbf{p}}_{gx}, \hat{\mathbf{p}}_{gy}$

Abilities

- Speed and Accuracy of trajectory generating and tracking pipeline
- Simplicity of CNN
- Test: Precision and Robustness
- Real Time Application
- Autonomous Flight through race track with moving gates with high agility
- Onboard Computation
- Agile Flight Trajectories
- Moving Gates
- Dynamic Environments
- No explicit map of environment required

Evaluation against:
- State-of-the-Art Navigation Methods
- Professional Human Drone Pilots

- Simulation/Real World

End-to-end ML Systems
Learning-based algorithms that couple perception and control

Motor commands directly derived from images
1-[25,27,14,4,24,13,11]

Abilities

- Independent of Global Maps
- Independent of Position Estimates

Shortcomings

- Inherent difficulties of generalizing to 3D motions 1-[25,4,24]
- High computational complexity 1-[27,11]
- Low maximum speed 1-[13]

Open Questions

Optimal Output Representation

- + High Robustness
- - Agility

Discrete Navigation Commands 1-[15,17]

Direct Control [14]

- + Agile control
- - High Sample Complexity

Perceptive Systems

Autonomous Systems

Challenges

- Optimal Control
- Localization and Mapping
- Dynamics Modeling
- Onboard Perception
- Trajectory Generation

Drone Racing

Valuable for autonomous systems which must fly safely and quickly through complex environments, i.e. disaster response, aerial delivery, inspection of complex structures).

Competitive control skills require years of training.

Human Pilot

Radio Transmitter

Drone Racing Sports
Video

Forward Facing Onboard Camera

Drone

Race Track

Static

Gates/Obstacles

Dynamic

Maintain Visual Contact to Gate

Look for Gate

Localize Relative to Gate

Tight Coupling of Perception and Control

1-[7,28]

Global Trajectory and State Estimation
State estimation must be accurate.

Challenges

Sensor Limits at High Speed

- Perceptual Aliasing
- Motion Blur
- Lighting Conditions

Expensive Sensors 1-[2]

Computational maps lead to drift 1-[18]

High Computational Costs 1-[22]

Designed for predominantly static worlds

Real-time performance onboard resource constrained platforms, i.e. small quadrotors

Difficulties in exploiting popular minimum-snap or -jerk trajectories 1-[19,20]

SLAM
Simultaneous Localization And Mapping
1-[3]

Accurate pose estimates against a globally consistent map are previously-generated.

Challenges

- High Computational Demands
- High Accelerations and Speeds
  - Motion Blur
  - Loss of Feature Tracking

Limits

Map created under different conditions

Predominantly static environments

Static Waypoints and Trajectories