Perception for robot autonomy

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Perception for robot autonomy

• From sensor features to plans and paths

• From sensor features to semantic interpretation

One perspective on the perception+autonomy challenges

• From sensor features to plans and paths
  – Learning and optimal control
  – Generating multiple options
  – Sequential processes

• From sensor features to semantic interpretation
  – The tractability challenge
  – Generating multiple hypothesis
  – Incorporating external knowledge sources and data
  – Limited computation
  – Deciding when to generate an output
  – Semi-supervised modeling
From sensor features to plans and paths: The pothole example
Local features: color, texture, …
+ Context features

How to map the features to control/decision policies?

From sensor features to plans and paths

- Even if we know an exact control model for the system:
  - Noisy data + not the right information
- Hard to model mapping from sensor data to actions and decisions
- Mapping depends on objective mission
- Learn mapping from data
Learning and optimal control

Learning to “optimally” map features to plans and paths
Optimal Control Solution

Learning ➔ Cost Map ➔ 2-D Planner ➔ Y
(Path to goal)
Mode 1: Training example

Mode 1: Learned behavior
Mode 1: Learned behavior
Mode 1: Learned cost map
Mode 2: Learned behavior
There is no single right mapping between sensor features and actions.

Mapping depends on subjective “operator” objectives.

Learning the mapping:
- Assume that behavior we wish to imitate can be recovered by a planning/optimal control algorithm.
- Generalization to handle noisy, imperfect behavior.
- Extension to strategic and multi-agent cases.
Generating and evaluating multiple alternatives

• (semi-)Optimal planning/decision given learned cost from sensor features may not be feasible
• In fact in general it is not possible
• Alternative:
  – Evaluate a set of alternatives with respect to the learned costs
Research questions: Optimize content and order of list

• Find “optimal” evaluation strategy for:
  – Relevance: Early items are highly likely to succeed
  – Diversity: Enough variation across early items such that redundancy is minimized

• Online operation

Sequential processes

Decisions are temporally dependent
Cannot learn from individual samples
Correlated errors leading to compounding effect
The dangers of optimistic models

- Training data sees (almost) only “good” examples → Optimistic modeling, overfitting, catastrophic failure

Example: Learning to drive

Worst-case quadratic growth in likelihood of errors over time

[D. Pomerleau circa 1987]
Results explore the fundamental role of interaction between a teacher and a student learning to mimic a task.

Formal results show decrease in the error as function of the number of training iterations.
Semantic interpretation

Mapping directly from sensor data to plans and paths may not be sufficient
Describing the environment in order to reason and make decisions
The tractability challenge

Off-line training: Model the distribution of labels vs. features
Run-time inference: Find most likely labels given model
Multiple hypothesis generation

Explaining decisions
Explaining mistakes

Perfect perception for robotics?

Visual input → Perception algorithms → Interpretation → Execution
Representing uncertainty in perception

Visual input → Perception algorithms → Interpretation → Application
Representing ambiguity

P(Class 1)  P(Class 2)
Incorporating external knowledge sources

Bottom-up processing from sensor data is not sufficient

Example

DoT Univ. Transportation Center
Using prior (approximate) maps

- How to combine uncertain labels from the map with perception output?
- Does it improve accuracy?
- How to represent the uncertainty?

Example: Uncertainty modeling

\[ P(\text{image label} = x | \text{external information} = x) = \]
Limited computation

Anytime processing
Distributed processing

Computation challenge

• Onboard computation resources may be insufficient for processing sensor data at high enough rate
• The situation may call for a (possibly partial) answer sooner than a full computation cycle
• Essential in robotics/autonomy applications
  – Computational performance is a dominant concern

• Anytime processing
• Distributed processing
Distributed perception processing

- Graceful degradation based on availability of computational nodes
- Automatic selection of onboard data and computation
- Fast switching

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