maeve
AUTOMATION

VISION-BASED NAVIGATION FOR AUTONOMOUS VEHICLES

BRIEF BIO

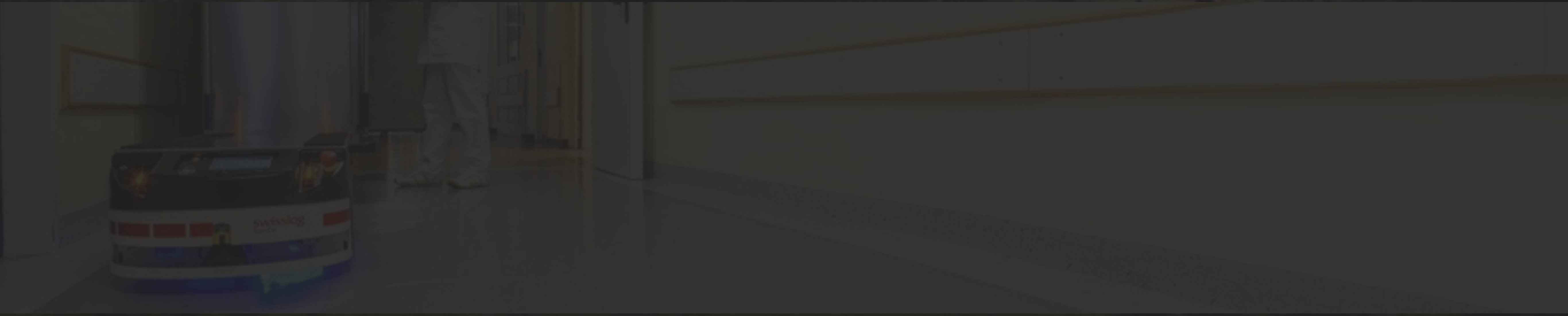
- B.Sc. CS
  Trine University
  2003
- M.Sc. CS
  Indiana University
  2012
- Ph.D. CS
  Indiana University
  2017
- Research Engineer, Bosch
  Highway Automated Driving
  2014
- Engineer, Apple Inc.
  Special Projects Group
  2016
- Senior Autonomy Engineer
  Uber ATG
  2018

OUTLINE

1. Robotics & the navigation problem
2. General approaches to control in stochastic systems
3. Complexity reduction through factorization
4. Vision-based representations for navigation
5. Example demonstration
6. Summary & future work

OUTLINE

ROBOTS & NAVIGATION



FUNDAMENTAL CHALLENGES

COMPLEXITY PROBLEMS

- I: Finite set of agents
- S: Finite set of states
- A: Finite set of actions
- T: Transition probability functions
- O: Observation function
- R: Reward function

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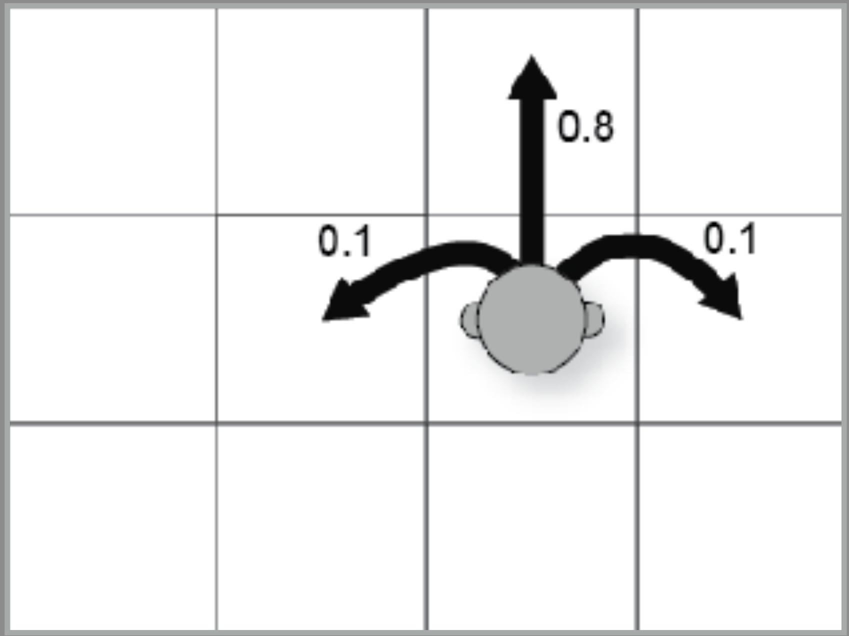

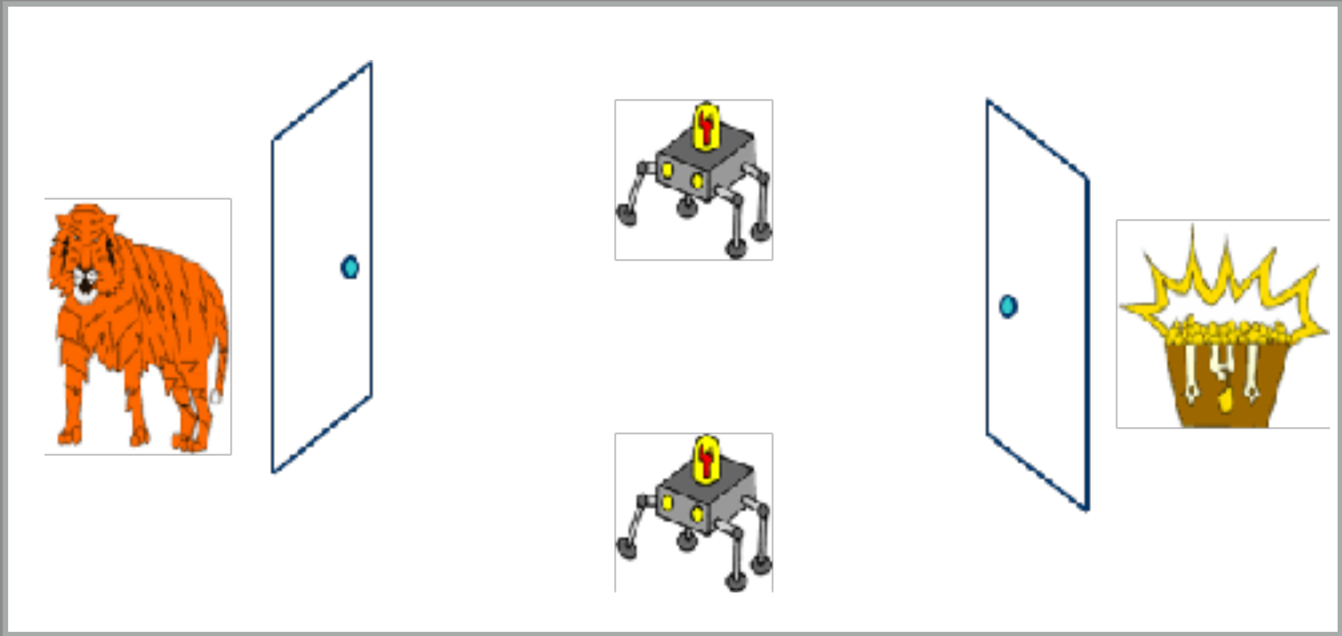

REPRESENTATION PROBLEMS

- Typical approaches occupancy and dynamics for objects in 3-space
- Sensor limitations can lead to poor quality estimates in this space
  - Lidar measures 3-space occupancy state, but has limited range
  - Radar measures 3-space dynamic state, but has limited visibility
- In image space, cameras provide data for both occupancy and dynamics with great range and visibility

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GENERIC STOCHASTIC SYSTEM

$$d\hat{\mathbf{x}} = f(t, \mathbf{x}_t, \mathbf{u}_t)dt + d\xi$$

GENERIC STOCHASTIC SYSTEM

Transition Control

$$d\hat{\mathbf{x}} = f(t, \mathbf{x}_t, \mathbf{u}_t)dt + d\xi$$

State change State Process Noise

GENERIC STOCHASTIC SYSTEM

- Generally, the state is not fully observable, so define transitions between distributions of state estimates

Observation

$$\mathbf{z}_t = (\hat{\mathbf{x}}_t, \theta_t)$$

Belief state

Distribution Parameters

GENERIC STOCHASTIC SYSTEM

- The optimal control minimizes the cost

Terminal cost

$$\hat{C}(\mathbf{z}_t, \mathbf{u}_{t:T}) = \left\langle \phi_T + \int_t^T R(\tau, \hat{\mathbf{x}}_\tau, \mathbf{u}_\tau) \, d\tau \right\rangle_{\mathbf{z}_t}$$

Immediate cost

GENERIC STOCHASTIC SYSTEM

- Unfortunately, many practical systems are difficult to solve (e.g. do no exhibit certainty equivalence)
- Approximation techniques can help
- The rollout method:

CONSTRAINED INTERFERENCE MINIMIZATION

- For an input control, compute the nearest output control that maintains a desired property with a given confidence

$$\mathbf{u}_t^\star = \arg\min_{\mathbf{u}} \mu(\mathbf{u}, \mathbf{u}_t^d)$$

$$\text{s.t.} \quad P(\text{good} \mid \mathbf{u}_t = \mathbf{u}) \geq \alpha$$

CONSTRAINED INTERFERENCE MINIMIZATION

$$P(\text{good} \mid \mathbf{u}_t = \mathbf{u}) \approx \int_{\mathbf{z}} S(\mathbf{x}, \mathbf{u}) p(\mathbf{x})$$

Indicator/
deterministic control problem

- Under Bayesian interpretation, Monte Carlo integration provides rigorous confidence bounds

CONSTRAINED INTERFERENCE MINIMIZATION

- The problem now approximates tractably:

$$
\begin{aligned}
\mathbf{u}_t^\star &= \arg\min_{\mathbf{u}} \mu(\mathbf{u}, \mathbf{u}_t^d) \\
\text{s.t.} \quad & \int_{\mathbf{z}} S(\mathbf{x}, \mathbf{u}) p(\mathbf{x}) \ \geq \alpha
\end{aligned}
$$

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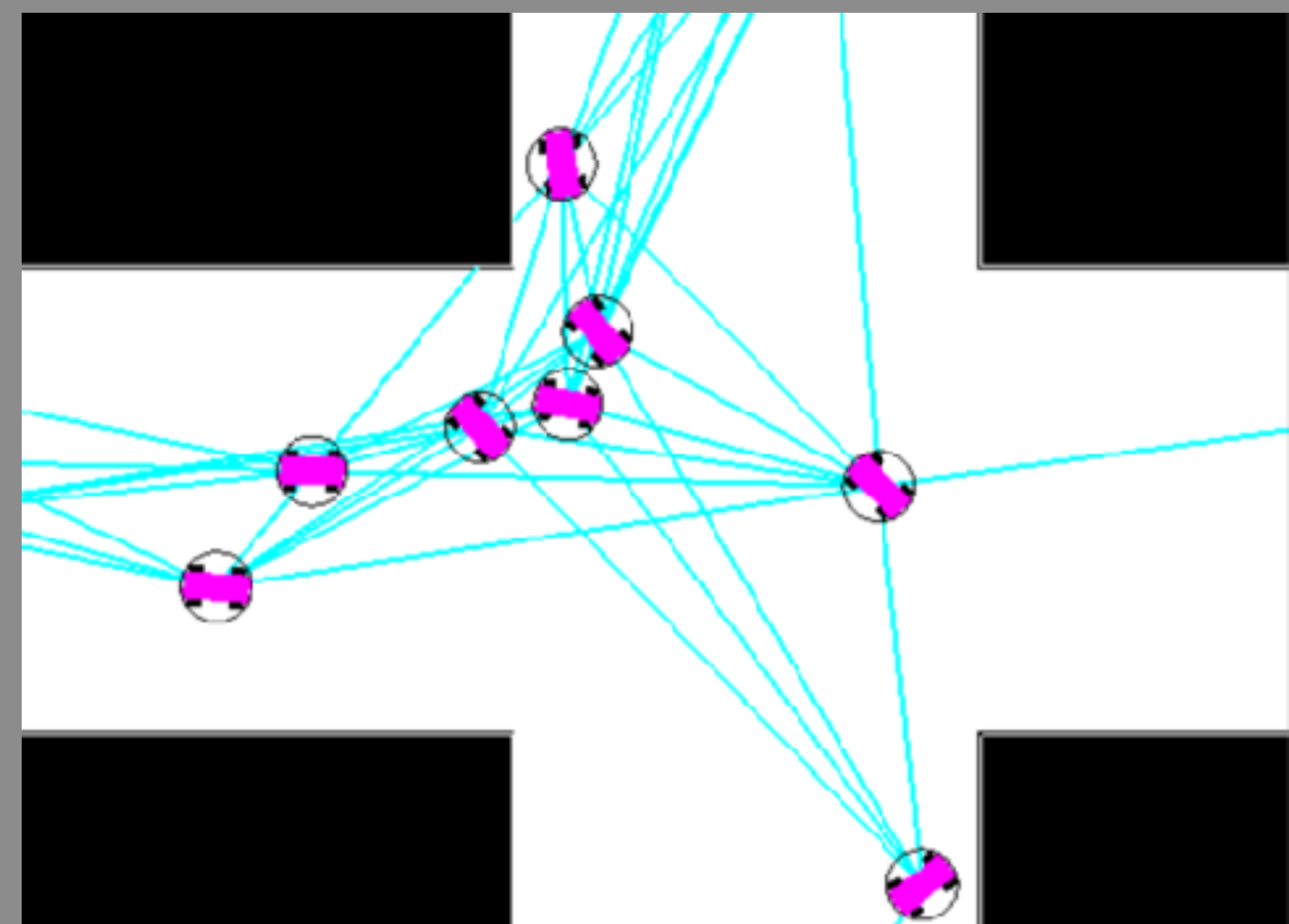
DYNAMICS AND COMPLEXITY: MOTIVATION

DYNAMICS AND COMPLEXITY: THE COORDINATION PROBLEM

Un-coordinated planning:
Reciprocal *n*-body collision avoidance

Jur van den Berg, et al.

Coordinated planning:
Safe distributed motion coordination



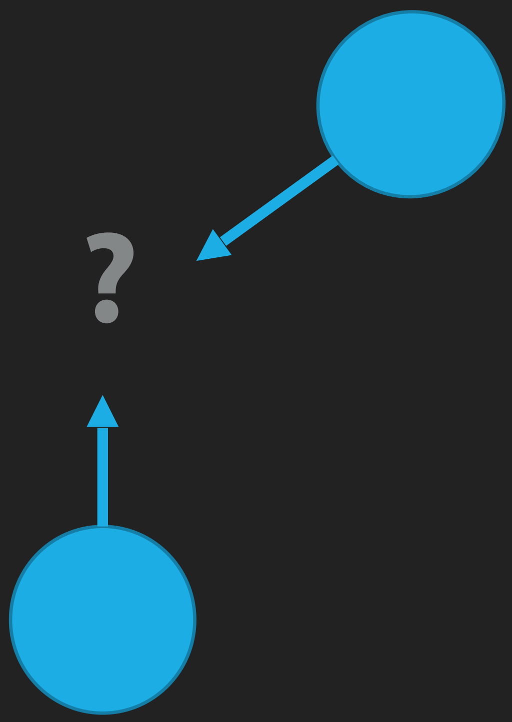
Kostas E. Bekris, et al.

DYNAMICS AND COMPLEXITY: PREMISES

1. **Optimality is not necessary**
   - These problems have no tractable optimal solution
2. **Agents are self-preserving**
   - Practical systems tend not to be demolition derbies
   - Self-preservation generally overwhelms other goals

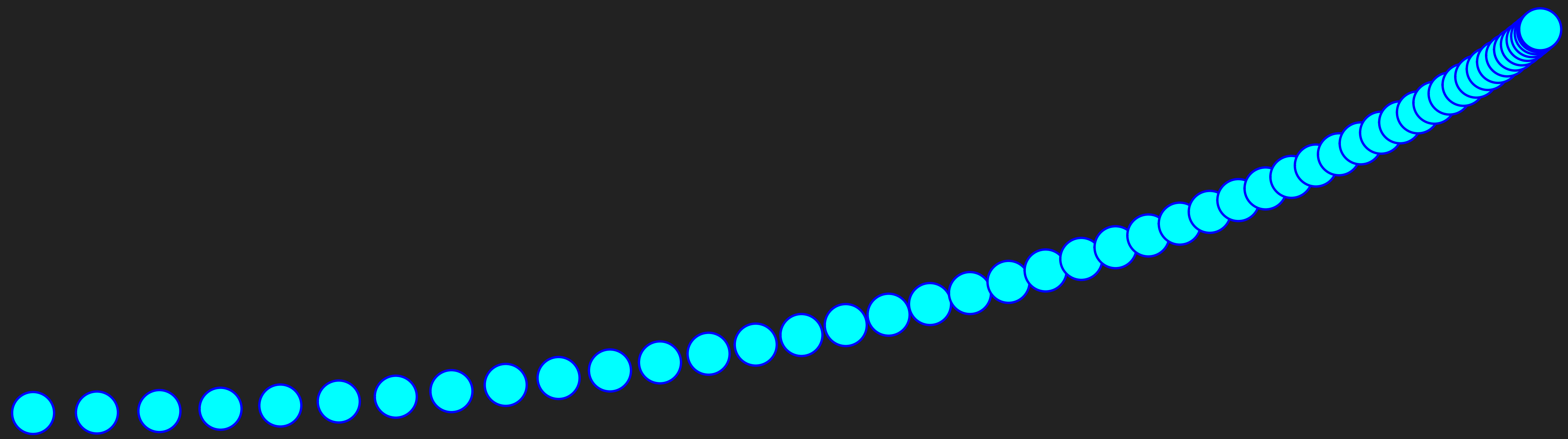
DYNAMICS AND COMPLEXITY: DEFINITIONS

- **Coordination:** The property that the feasibility of two actions cannot be verified independently of each other



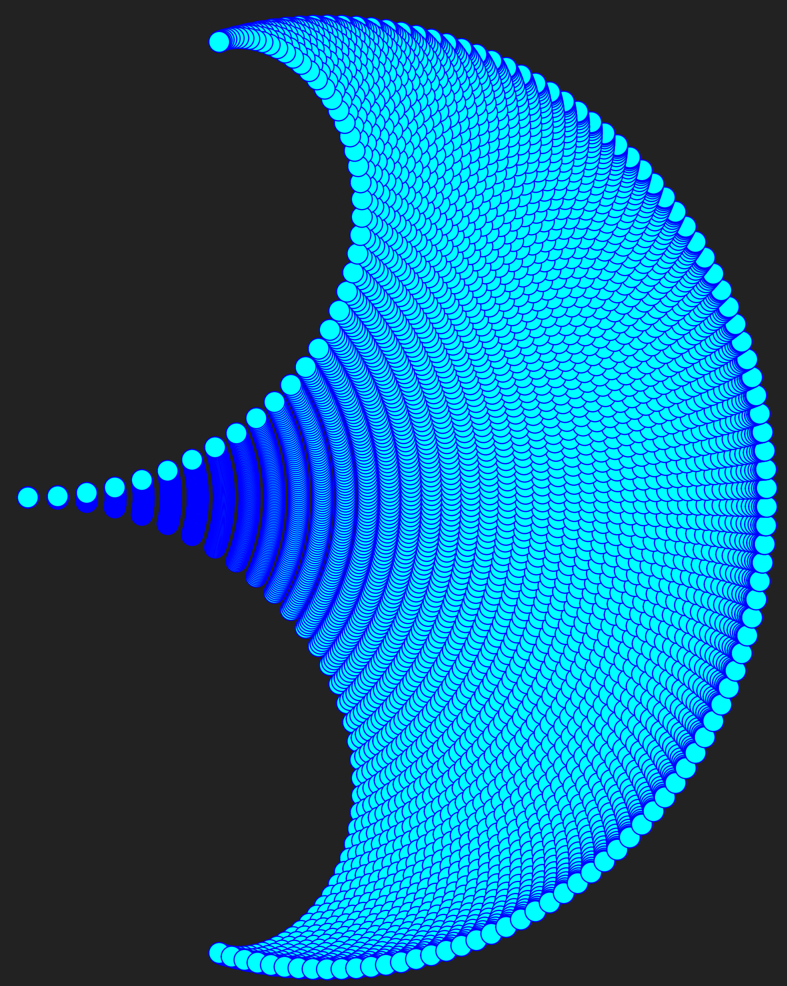
DYNAMICS AND COMPLEXITY: DEFINITIONS

- **Stopping Path (SP):** The minimal set of states an agent must occupy while coming to zero velocity along the path



DYNAMICS AND COMPLEXITY: DEFINITIONS

- **Stopping Region (SR):** The union of all stopping paths over the set of feasible paths



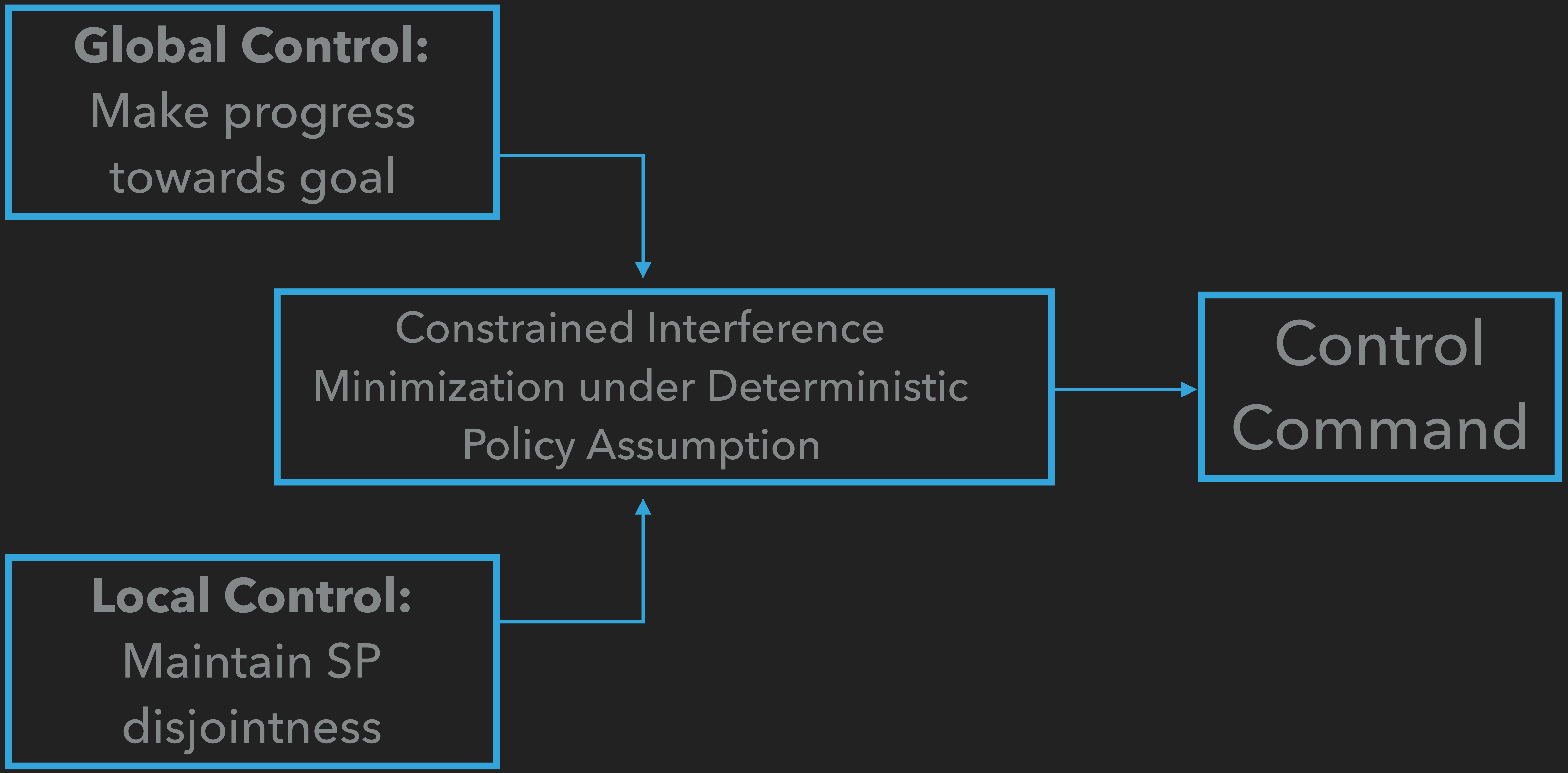
DYNAMICS AND COMPLEXITY: MAIN RESULT

- *A multi-agent system is guaranteed to be able to remain collision free without coordination if all agents have a SP that is disjoint from all others' SRs.*
- SPs & SRs are an important representation because:
  - They are computable independent of agent intent
  - They can be manipulated by each agent
  - Thus, a system can self-organize away from a coordination requirement

FACTORING INTERACTIONS EFFECTS

- The SR and SP concepts enables interaction effects to be factored out of navigation problems
- Once factored, deterministic policies can be assumed for other agents (this provides a deterministic heuristic)
- **Selective Determinism** uses the deterministic heuristic to formulate navigation as constrained interference minimization
- *Now, deterministic control can be used in stochastic systems!*

THE SELECTIVE DETERMINISM FRAMEWORK



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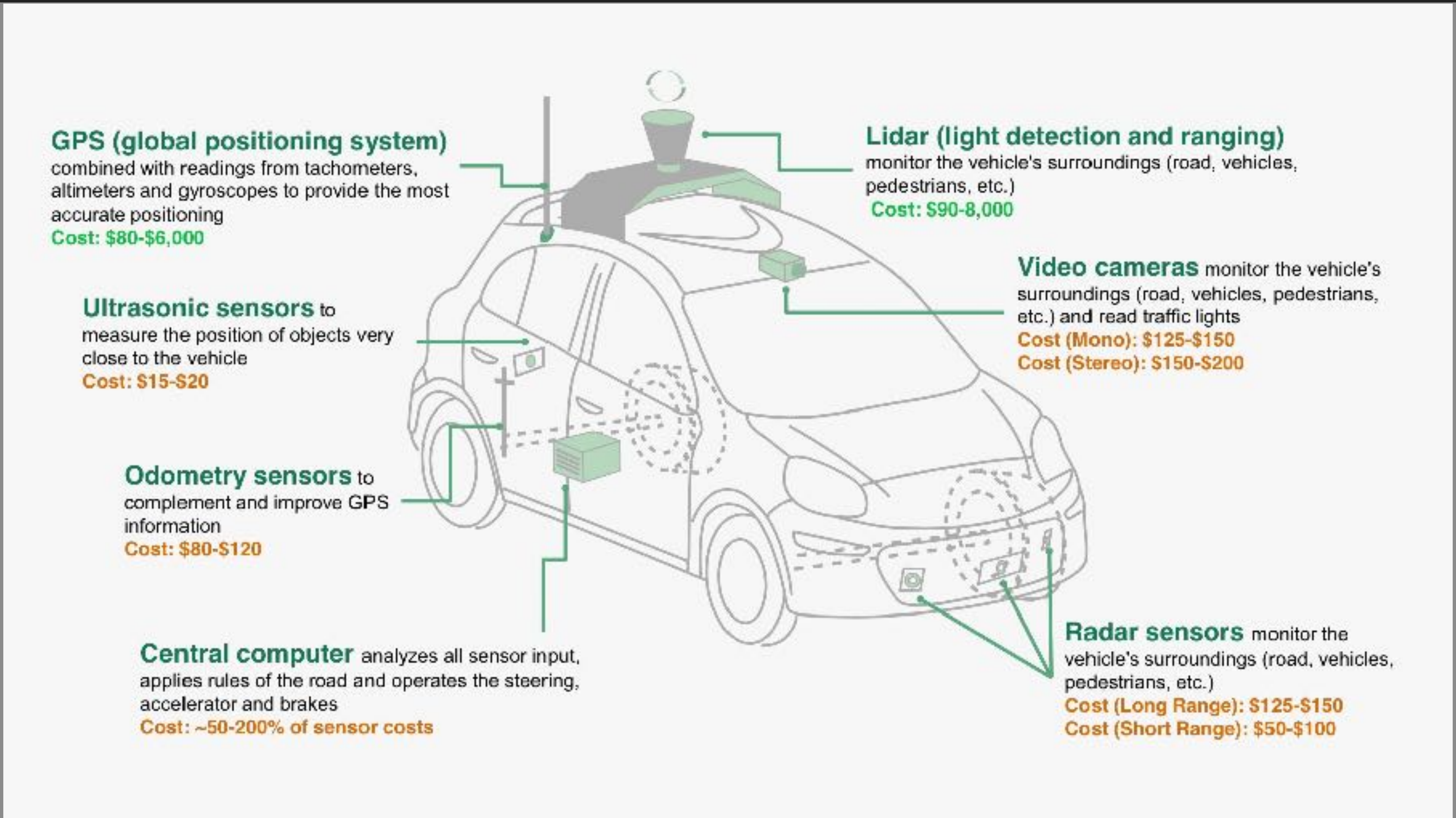
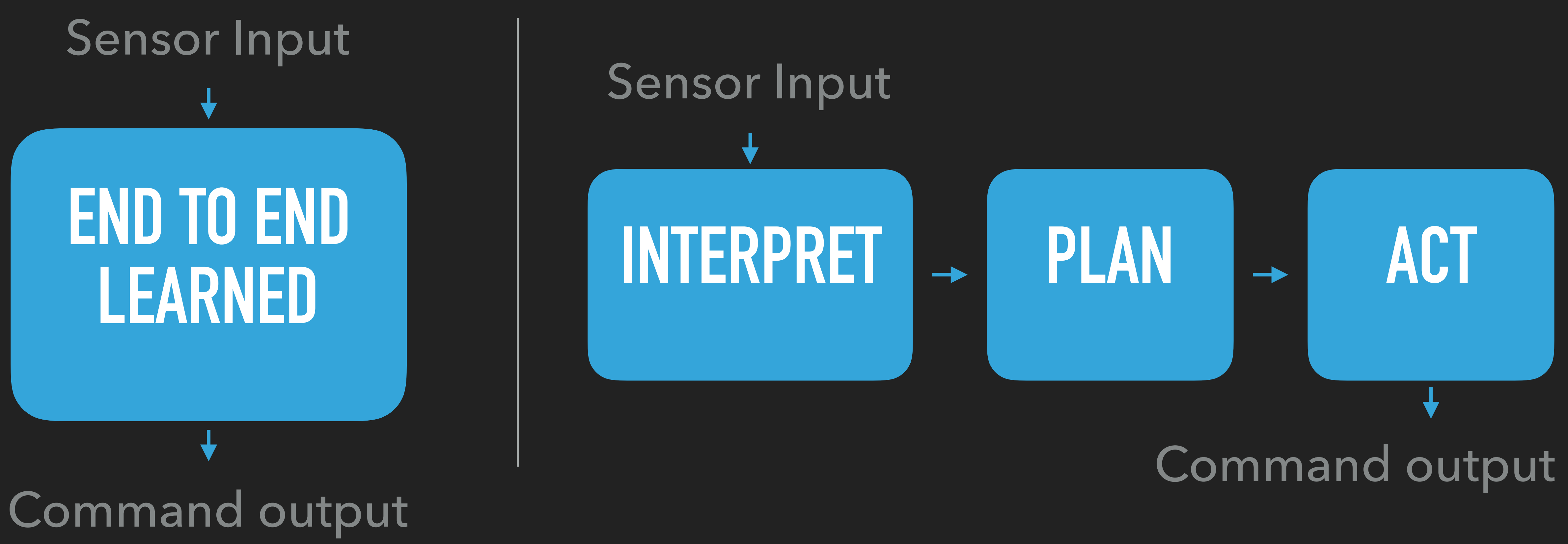
VISION-BASED NAVIGATION FOR AUTONOMOUS VEHICLES



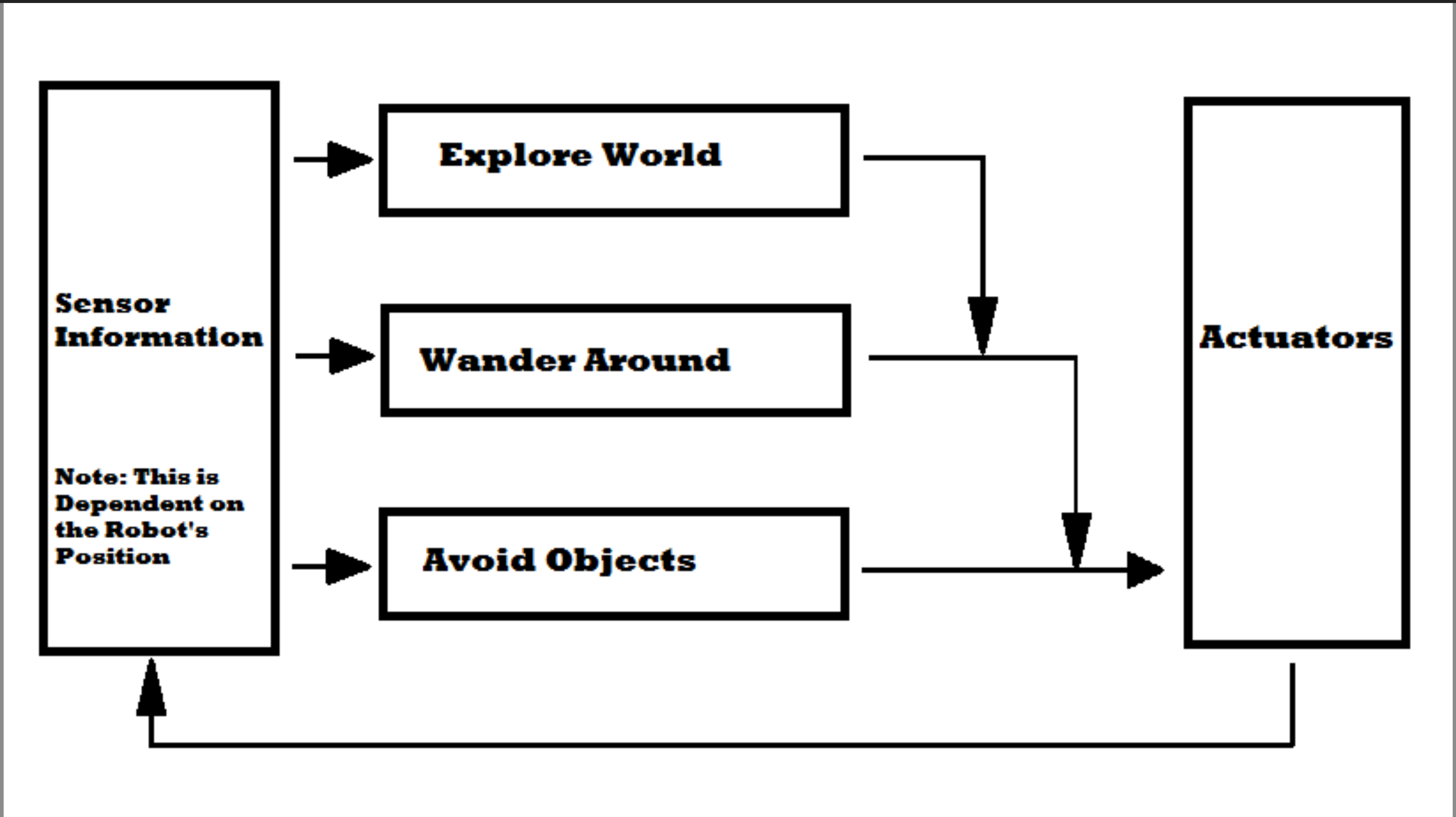
https://www.wired.com/2015/04/cost-of-sensors-autonomous-cars/

MOBILE AGENT CONTROL ARCHITECTURES

- Two predominant modern architectures for control:



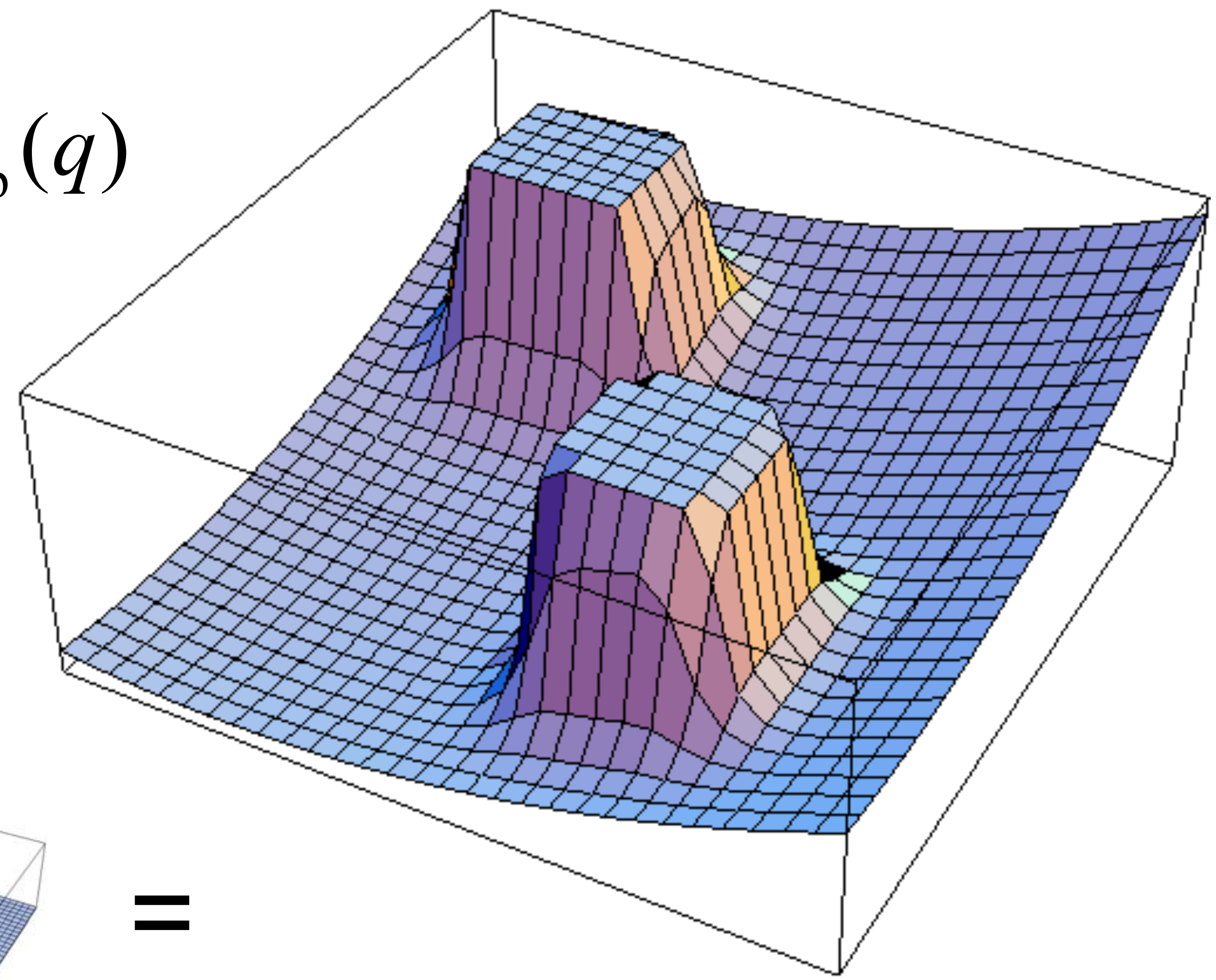
SUBSUMPTION ARCHITECTURE

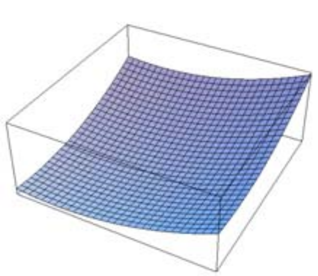
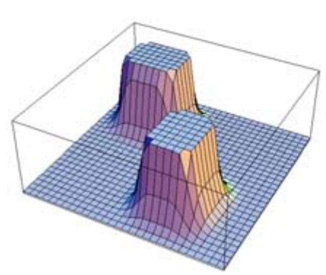


ARTIFICIAL POTENTIAL FIELDS

$$U(q) = U_{\text{att}}(q) + U_{\text{rep}}(q)$$

$$F(q) = -\nabla U(q)$$



 +  =

SUBSUMPTION WITH POTENTIAL FIELDS

- Potential fields implement subsumption architectures
- Problem: what about minima and occlusions?

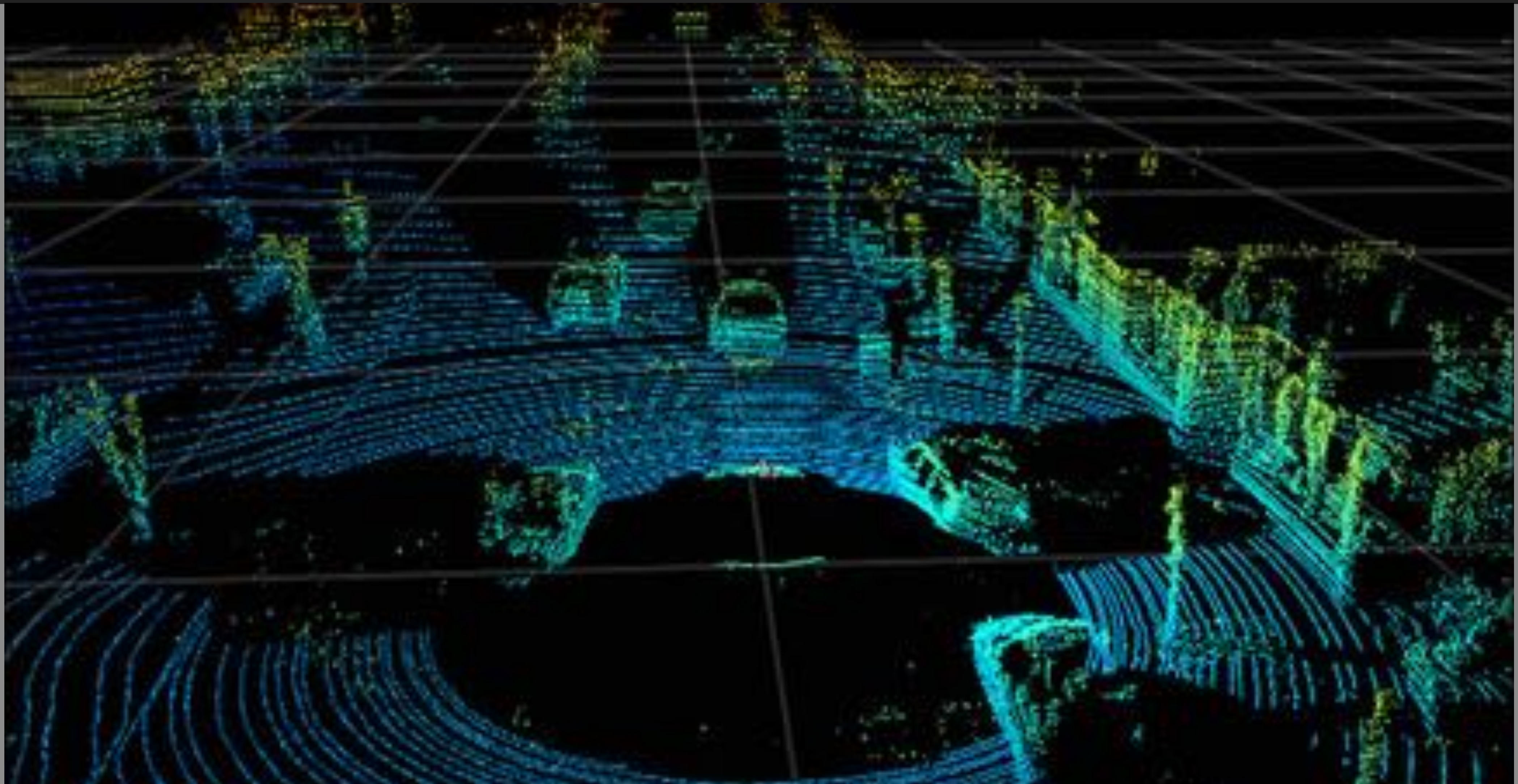
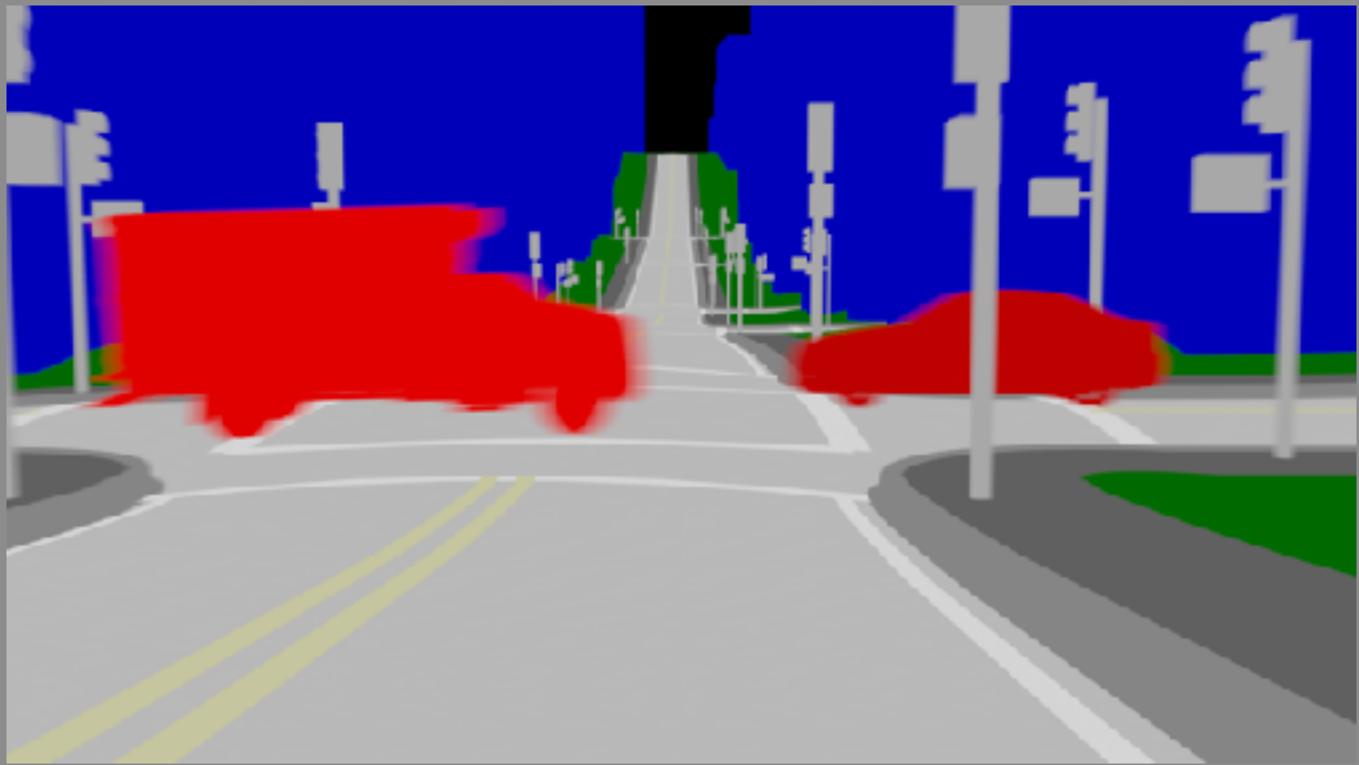


IMAGE SPACE

- Long-range visibility makes it easier to escape minima
- Occlusions do not occur in image space: The sensor can see the entire space it is measuring



Renders provided by [Parallel Domain]

THE IMAGE SPACE POTENTIAL FIELD

- A potential field defined over image space
- Finite in size, discretely indexed
- Potential function ranges over affinely extended reals:

$$I(x, y) \mapsto \overline{\mathbb{R}}^2$$

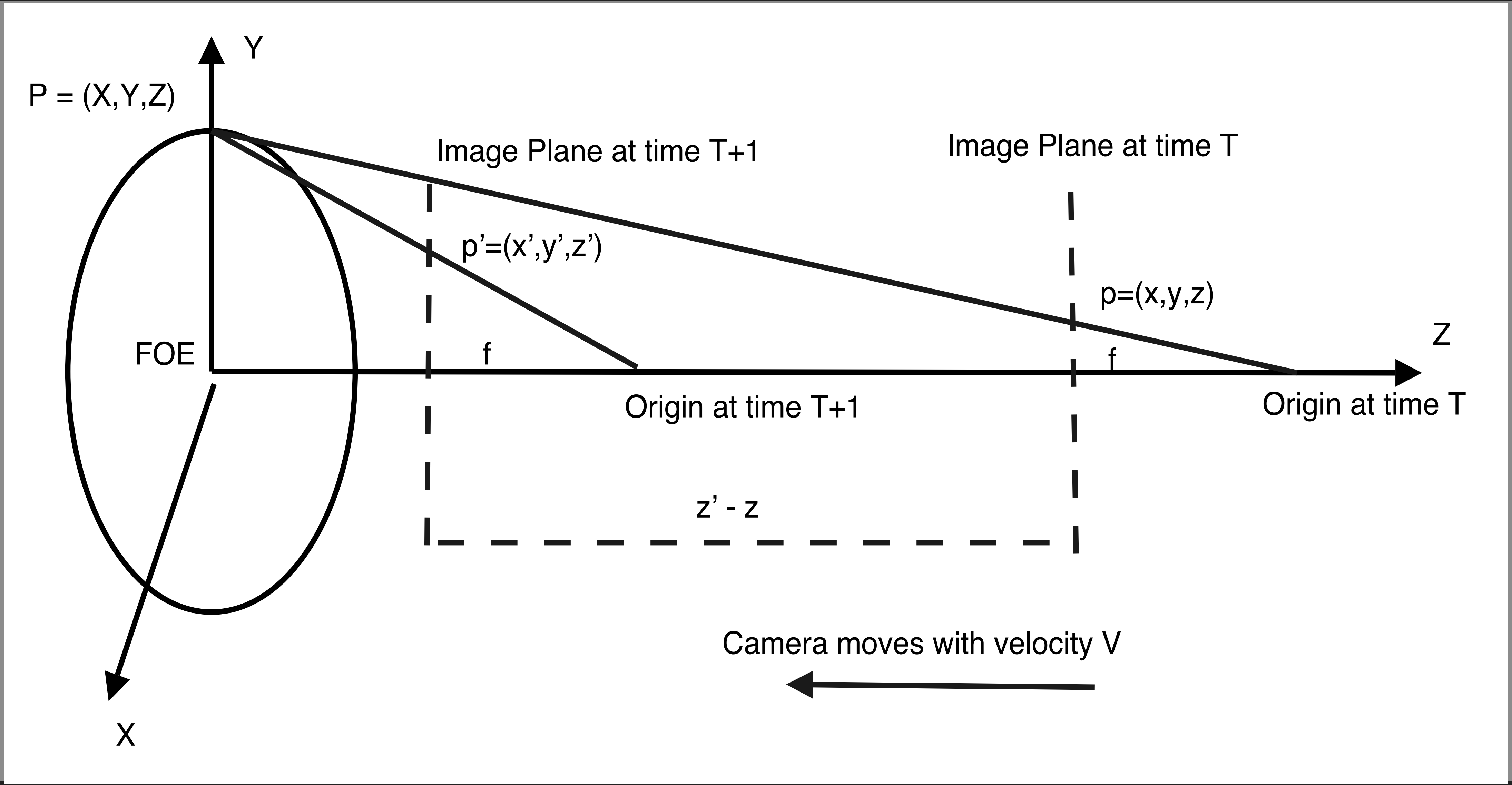
POTENTIAL FIELD ALGEBRA

- All fields have like infinities with like signs
- Scalar multiplication only for finite, non-negative values
- Element-wise multiplication only by finite, non-negative scalar fields

Under these rules sums of fields, or sums of scaled fields, preserve infinite values, which can be used to represent hard constraints

TIME-TO-CONTACT FOR HARD CONSTRAINTS

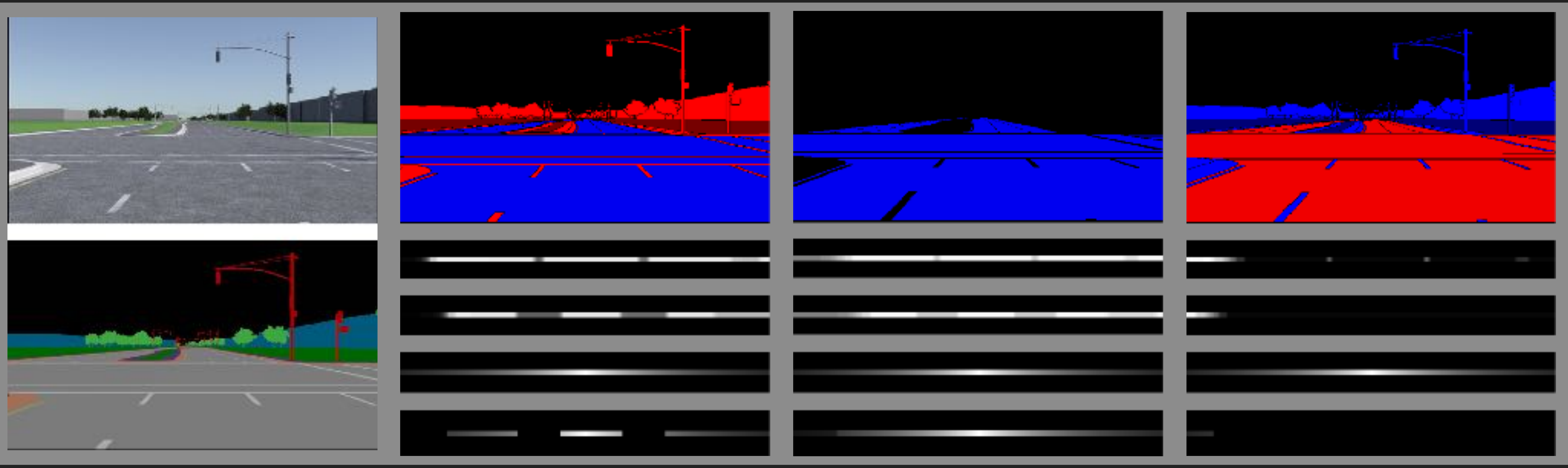
- Range cannot be measured directly in image; TTC can



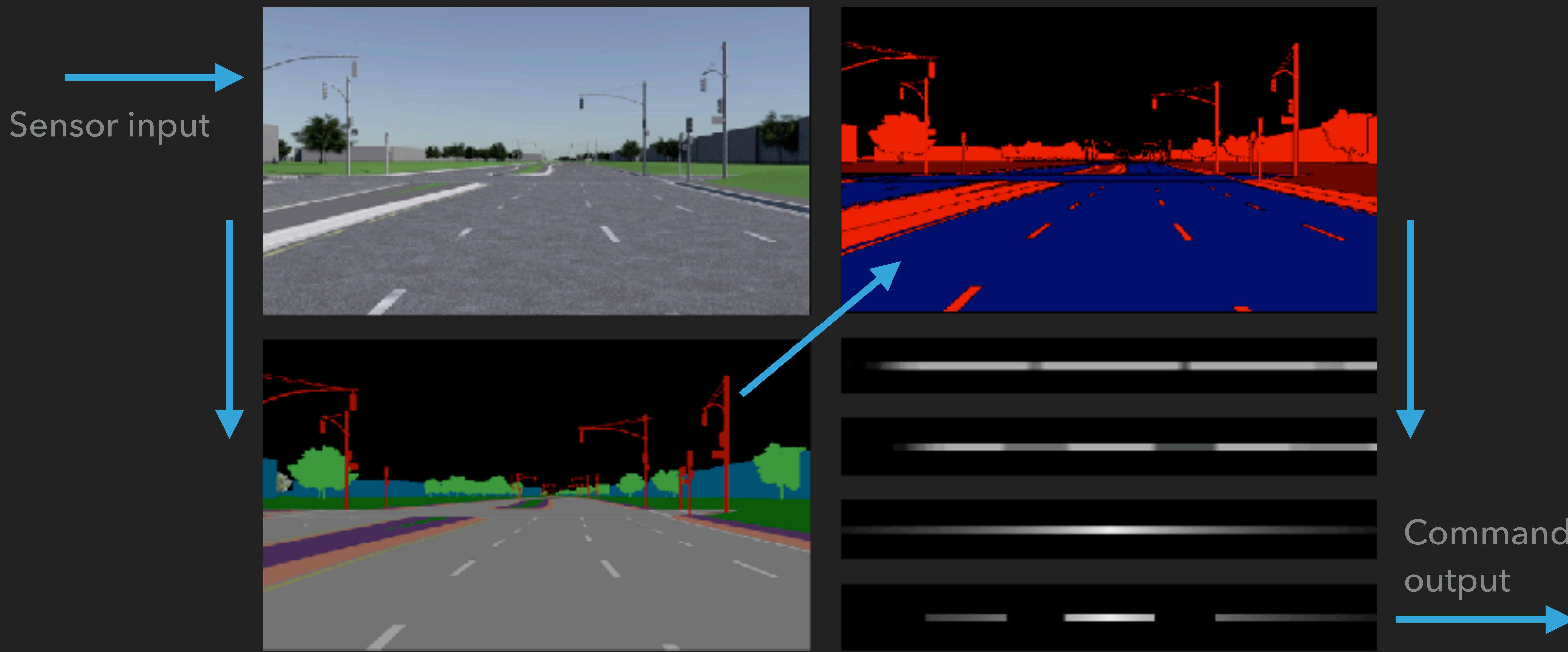
Peter O'Donovan, Optical Flow: Techniques and Applications

GUIDANCE VALUES FOR SOFT CONSTRAINTS

- These finite values can come from heuristics, users, or ML
- Algebra ensures hard constraints are uncorrupted



CONTROL WITH IMAGE SPACE POTENTIAL FIELDS



Camera images (top) are segmented by perception (bottom)

The segmentation is projected into a potential space (top) and iteratively transformed into control space (bottom)

CONTROL WITH IMAGE SPACE POTENTIAL FIELDS

- **Conjecture:**
  A minimum time headway can be witness for SP disjointness
- **Implication:**
  Labeled monocular camera input suffices to solve non-adversarial, non-cooperative multi-agent navigation problems!

- Academically this is surprising; but experience strongly suggests this possibility

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Demonstration

Image Space Potential Fields for Mobile Navigation with Subsumption-based Visual Servoing Control Architectures

- This demonstrates a navigation problem in which global guidance subsumes local collision avoidance
- The guidance command attempts to command the vehicle straight forward at all times
- The collision avoidance routine maintains sets of safe control commands at all times
- At all times, the vehicle controller executes the member of the collision avoidance control set nearest the guidance control
- Thus, the system remains collision free even when the guidance control would otherwise cause collision

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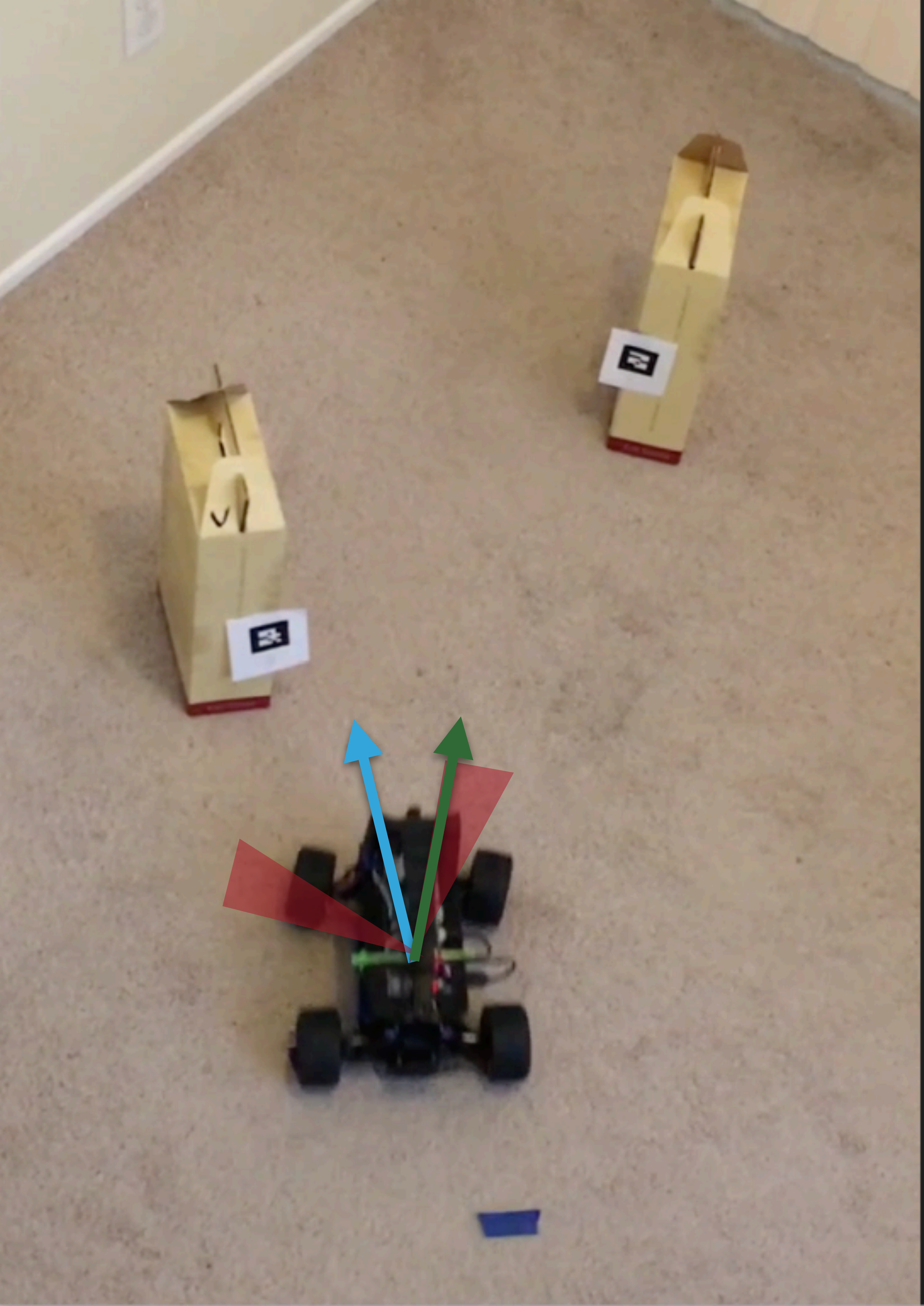

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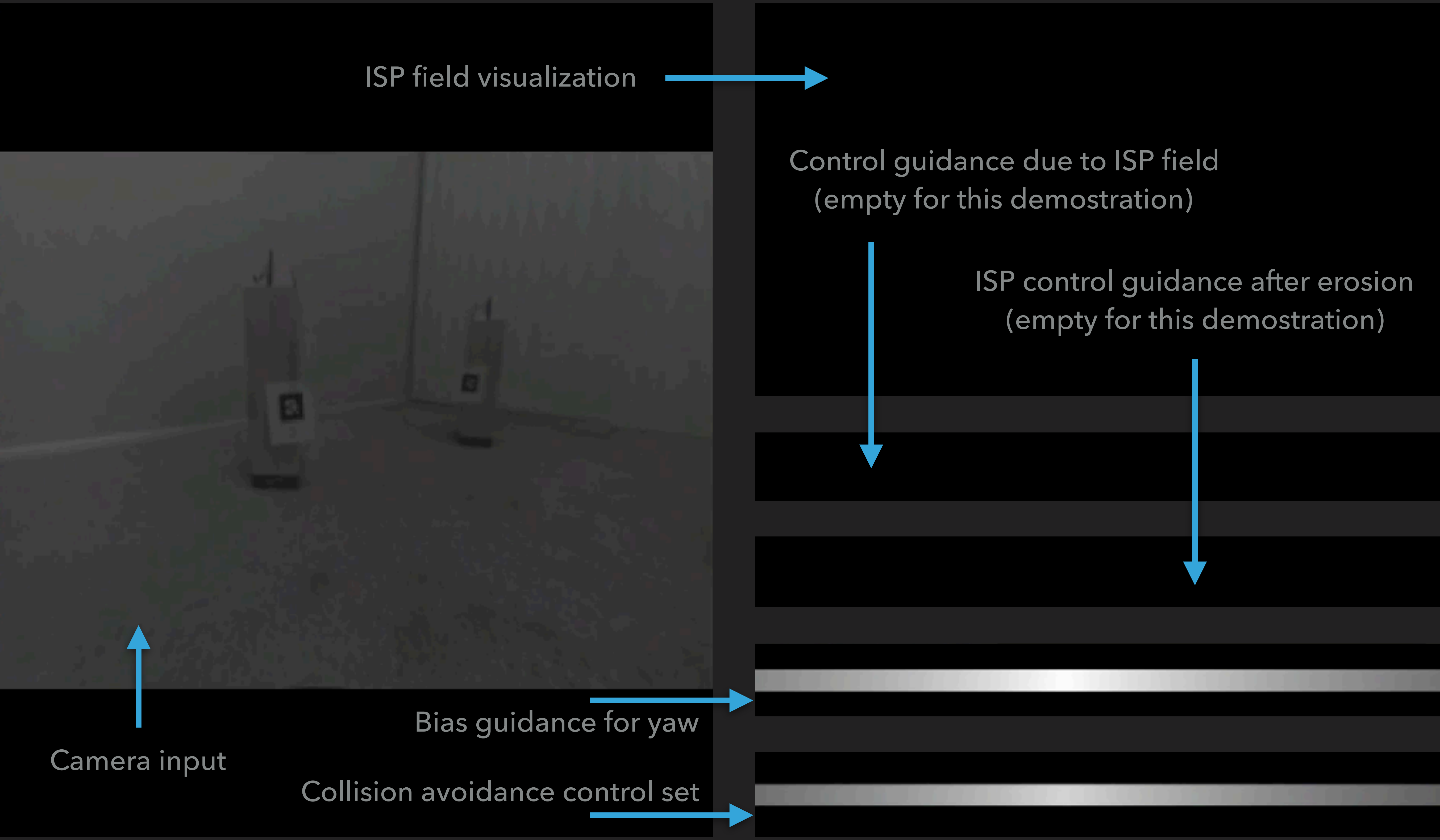

Video of the scenario from the vehicle POV

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SUMMARY & FUTURE WORK

- Potential field control laws:
  - Better coupled control
  - Incorporate multiple cameras
- Several conjectures deserve further investigation
- **BUT:** The real problem is ***perception***:
  What am I looking at, and where is it? This is key.

DATA SETS, CODE, & MORE INFORMATION

https://maeveautomation.org/development/