

A robotic car is shown navigating a track constructed from wooden blocks. A glowing blue trajectory is overlaid on the track, illustrating the path of the car. The background is dark, and the track is illuminated by the car's lights and the glowing trajectory.

# Trajectory Optimization for Ergodic Control

Ian Abraham

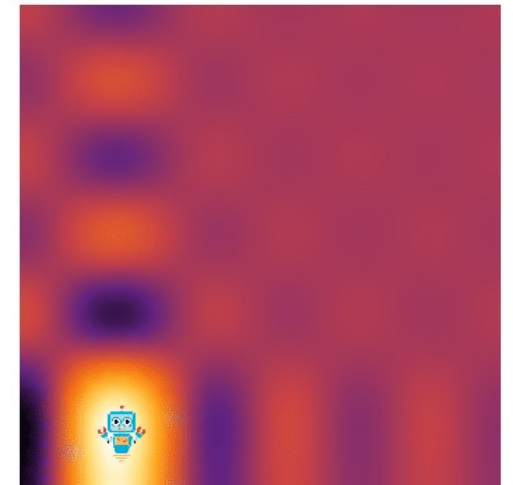
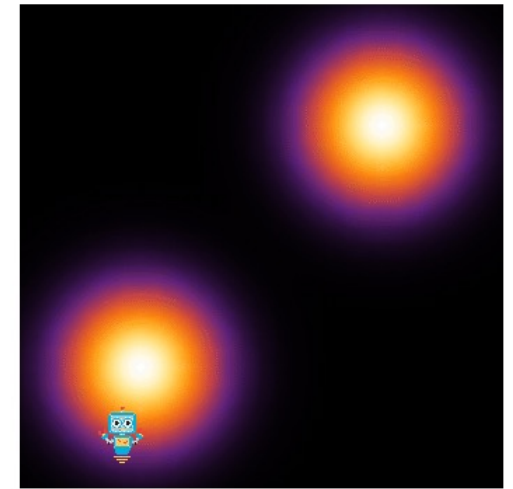
Yale SCHOOL OF ENGINEERING  
& APPLIED SCIENCE



# Introduction to Ergodic Coverage

## Ergodic Exploration/Search

- Goal: achieve ergodic dynamics over bounded area
- Approach: optimize ergodic metric over trajectories
  - Nonlinear/nonconvex problem
  - Many “good” local minima
  - Extendable to arbitrary constraints
- Independent of robot dynamics/spatial scale/sensor/information measure
- Non-Myopic Exploration (formulated over long planning horizons)



[1] Miller, Lauren M., Yonatan Silverman, Malcolm A. MacIver, and Todd D. Murphey. "Ergodic exploration of distributed information." IEEE Transactions on Robotics 32, no. 1 (2015): 36-52.

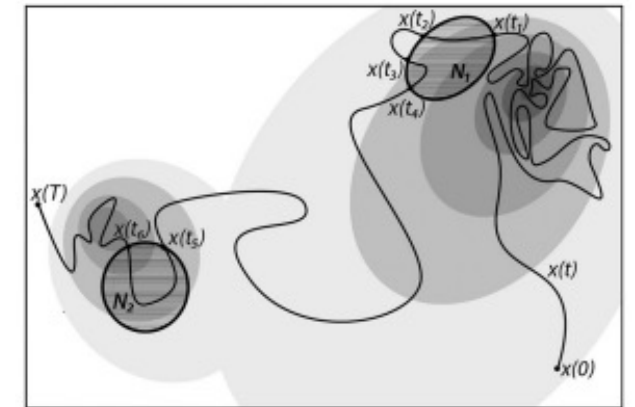
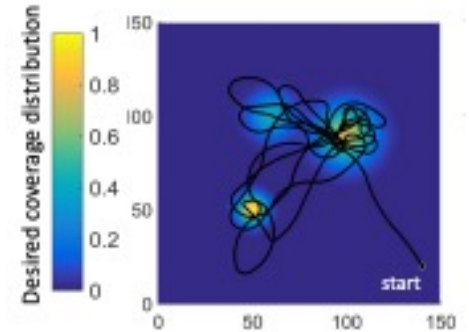
[2] Lerch, Cameron, Dayi Dong, and Ian Abraham. "Safety-critical ergodic exploration in cluttered environments via control barrier functions." In 2023 IEEE International Conference on Robotics and Automation (ICRA), pp. 10205-10211. IEEE, 2023.

# Introduction to Ergodic Coverage

## Ergodic Coverage

- A trajectory is said to be ergodic if, **on average**, it spends time in regions **proportional to the utility of exploring** said area
- For  $t_f \rightarrow \infty$ , ergodic trajectories guarantee complete coverage

$$\lim_{t_f \rightarrow \infty} \frac{1}{t_f} \int_0^{t_f} \phi(g \circ x(t)) dt = \int_{\mathcal{W}} \phi(w) \mu(w) dw$$



[1] Ayvali, Elif, Hadi Salman, and Howie Choset. "Ergodic coverage in constrained environments using stochastic trajectory optimization." 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2017.

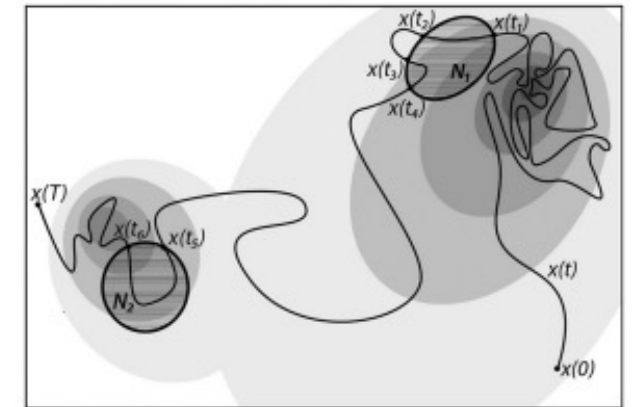
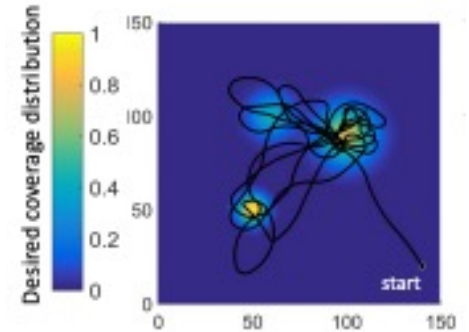
[2] Miller, Lauren M., et al. "Ergodic exploration of distributed information." IEEE Transactions on Robotics 32.1 (2015): 36-52.

# Introduction to Ergodic Coverage

## Ergodic Coverage

- An ergodic metric computes the distance to ergodicity
- Can be computed in the Fourier domain
  - Trajectory measure defined as Dirac delta function

$$\begin{aligned}\mathcal{E}_\mu(x) &= \sum_{k \in \mathcal{K}^v} \Lambda_k \left( c_{t_f}^k - \mu^k \right)^2 \\ &= \sum_{k \in \mathcal{K}^v} \Lambda_k \left( \frac{1}{t_f} \int_0^{t_f} F_k(g \circ x(t)) dt - \int_{\mathcal{W}} F_k(w) \mu(w) dw \right)^2\end{aligned}$$



[1] Ayvali, Elif, Hadi Salman, and Howie Choset. "Ergodic coverage in constrained environments using stochastic trajectory optimization." 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE, 2017.

[2] Miller, Lauren M., et al. "Ergodic exploration of distributed information." IEEE Transactions on Robotics 32.1 (2015): 36-52.

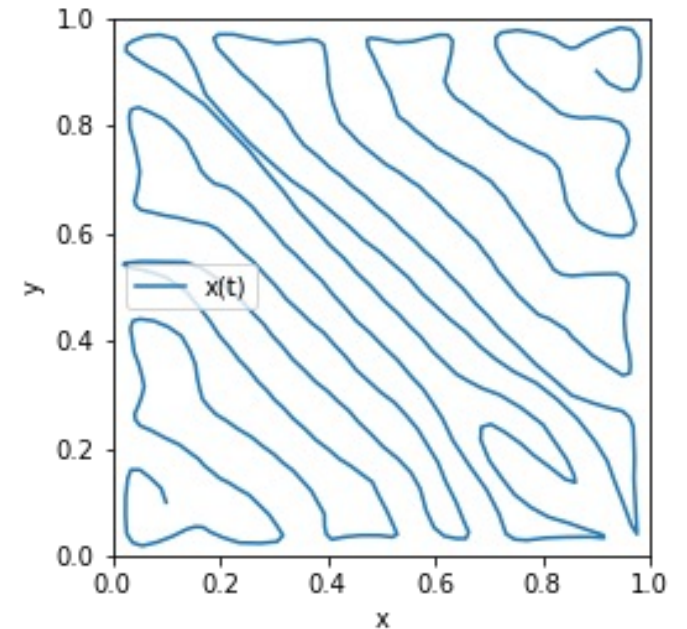


# Ergodic Trajectory Optimization

## Ergodic Trajectory Optimization

- Ergodic metric can be included in common trajectory optimization formulations

$$\min_{x(t), u(t)} \left\{ \mathcal{E}(x(t), \mu) + \int_0^{t_f} u(t)^\top \mathbf{R} u(t) dt \right\}$$
$$\text{s.t.} \quad \begin{cases} x(t) \in \mathcal{X}, u(t) \in \mathcal{U}, g \circ x(t) \in \mathcal{W}, \quad \forall t \\ x(0) = x_0, x(t_f) = x_f \\ \dot{x} = f(x, u) \\ h_1(x, u) \leq 0, h_2(x, u) = 0 \end{cases}$$



Uniform coverage on 2D workspace based on continuous ergodic coverage

# Approach 1: iLQR, DDP

$$\begin{aligned}\mathcal{E}_\mu(x) &= \sum_{k \in \mathcal{K}^v} \Lambda_k \left( c_{t_f}^k - \mu^k \right)^2 \\ &= \sum_{k \in \mathcal{K}^v} \Lambda_k \left( \frac{1}{t_f} \int_0^{t_f} F_k(g \circ x(t)) dt - \int_{\mathcal{W}} F_k(w) \mu(w) dw \right)^2\end{aligned}$$

## Requires First Derivative Information

- Problem not in Bolza form
- Its derivative is!

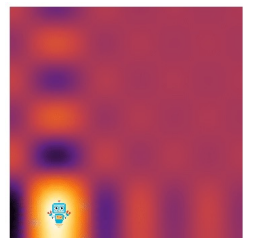
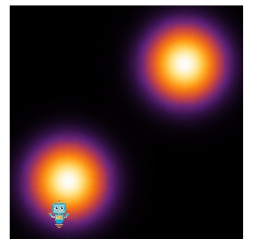
$$D\mathcal{E}_\mu(x(t)) \cdot \delta x(t) = 2 \sum_{k \in \mathcal{K}^v} \Lambda_k \left( c_{t_f}^k - \mu^k \right) \cdot \frac{1}{t_f} \int_0^{t_f} DF_k(g \circ x(t)) \cdot \delta x(t) dt$$

$$\implies 2 \sum_{k \in \mathcal{K}^v} \Lambda_k \left( c_{t_f}^k - \mu^k \right) \cdot \frac{1}{t_f} DF_k(g \circ x(t)) \cdot \delta x$$

$$DF_k(g \circ x) = \frac{dF_k(w)}{dw} \frac{dg(x)}{dx}$$

## Plug and Play Into Traj Opt. Solver

- Add in control costs as needed
- Choose your integration



# Approach 2: Discretize then Optimize

## Approach

- We solve problem over **discrete** trajectories
- Form a discrete-time ergodic metric

$$\mathcal{E}(x(t), \mu) \approx \hat{\mathcal{E}}(\mathbf{x}, \mu) = \sum_{k \in \mathcal{K}^v} \Lambda_k (c^k(\mathbf{x}) - \mu^k)^2$$

$$= \sum_{k \in \mathcal{K}^v} \Lambda_k \left( \frac{1}{T} \sum_{t=0}^{T-1} \underline{F_k(g \circ x_t)} - \mu^k \right)^2$$

$$\mathbf{x} = [x_0, x_1, \dots, x_{T-1}]$$

$$\mathbf{u} = [u_0, u_1, \dots, u_{T-1}]$$

$$T = \frac{t_f}{dt}$$

$$\begin{aligned} x_{t+1} &= F(x_t, u_t) \\ &= x_t + \Delta t f(x_t, u_t) \end{aligned}$$

# Approach 2: Discretize then Optimize

## Approach

- We solve problem over **discrete** trajectories
- Form a discrete-time ergodic NLP

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{u}} \quad & \hat{\mathcal{E}}(\mathbf{x}, \mu) + \sum_{t=0}^{T-1} \ell(x_t, u_t) \\ \text{s.t.} \quad & \begin{cases} x_t \in \mathcal{X}, u_t \in \mathcal{U}, g(x_t) \in \mathcal{W}, \forall t \\ x_0 = \tilde{x}_0, x_T = \tilde{x}_f \\ x_{t+1} = x_t + \Delta t f(x_t, u_t) \\ h_1(\mathbf{x}, \mathbf{u}) \leq 0, h_2(\mathbf{x}, \mathbf{u}) = 0 \end{cases} \end{aligned}$$

$$\begin{aligned} \mathcal{E}(x(t), \mu) &\approx \hat{\mathcal{E}}(\mathbf{x}, \mu) = \sum_{k \in \mathcal{K}^v} \Lambda_k (c^k(\mathbf{x}) - \mu^k)^2 \\ &= \sum_{k \in \mathcal{K}^v} \Lambda_k \left( \frac{1}{T} \sum_{t=0}^{T-1} F_k(g \circ x_t) - \mu^k \right)^2 \end{aligned}$$

## Plug and Play Into Opt. Solver

- Hessian not very friendly
- Approx. Newton's method works
- LBFGS
- Choose your own discretization/colocation

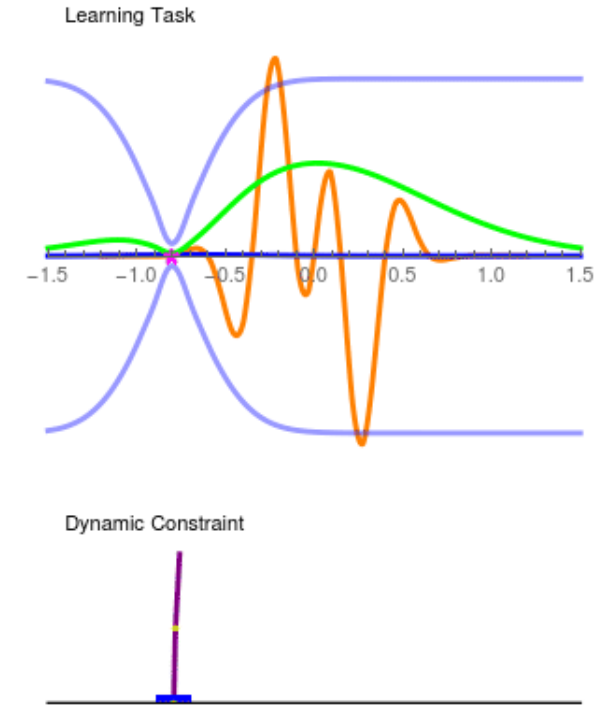
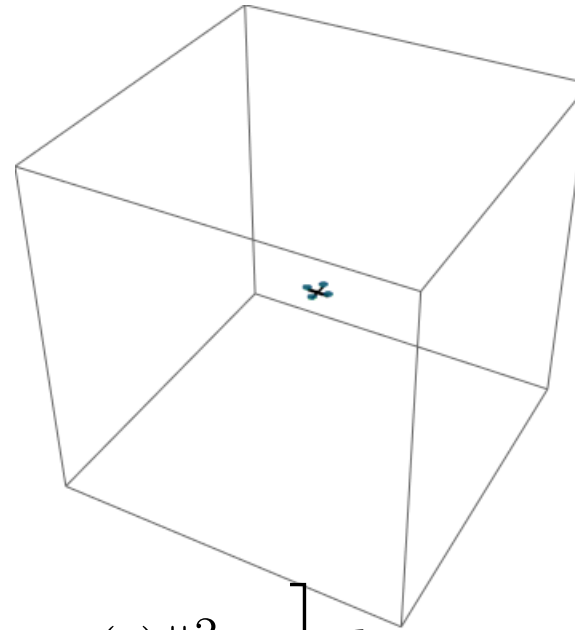


# Approach 3: Sample-based (TBD Later)

## Approach

- Optimize problem through sample-based optimization!
- Very fast, but less accurate

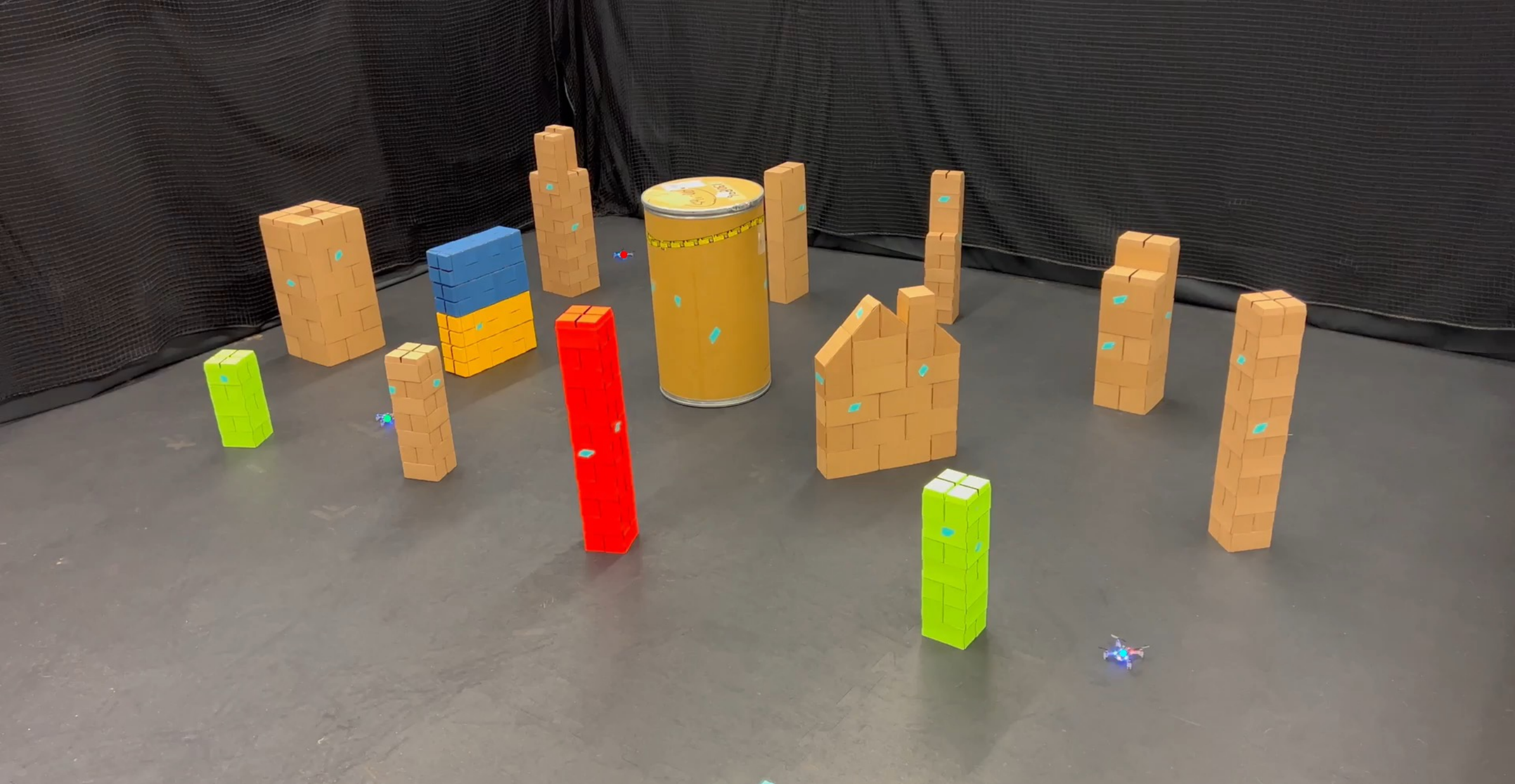
$$\begin{aligned} D_{KL}(p||q) &= -E_{p(s)}[\log q(s)] \\ &\approx -\sum_{i=1}^N p(s_i) \log q(s_i) \\ &\propto -\sum_{i=1}^N p(s_i) \log \int_{t_0}^{t_f} \exp \left[ -\frac{1}{2} \|s_i - \bar{x}(t)\|_{\Sigma^{-1}}^2 \right] dt, \end{aligned}$$



A small drone with blue and red lights is flying in a dark grey environment. The environment contains several obstacles: a red rectangular block, a green rectangular block, and several brown cardboard boxes of various sizes. A black mesh curtain is visible in the background. A dark blue horizontal band with white text is overlaid across the middle of the image.

# Uniform Coverage with Multiple Drones and Safety Constraints

Multi-drone ergodic search with drone-drone and drone-obstacle avoidance using



Multi-drone ergodic search with drone-drone and drone-obstacle avoidance using <sup>11</sup> QBF