Physics-Driven Machine Learning for Time-Optimal Path Planning in Stochastic Dynamic Flows

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Submission 11

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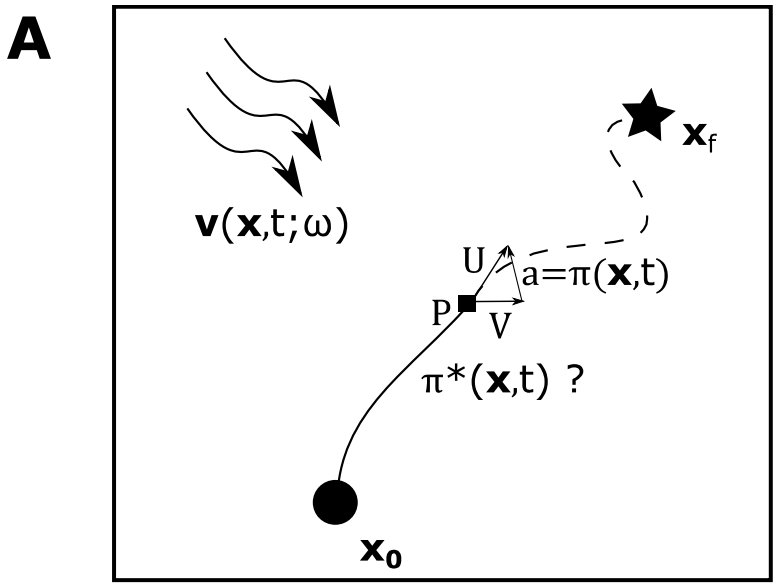
Path Planning for Autonomous Agents

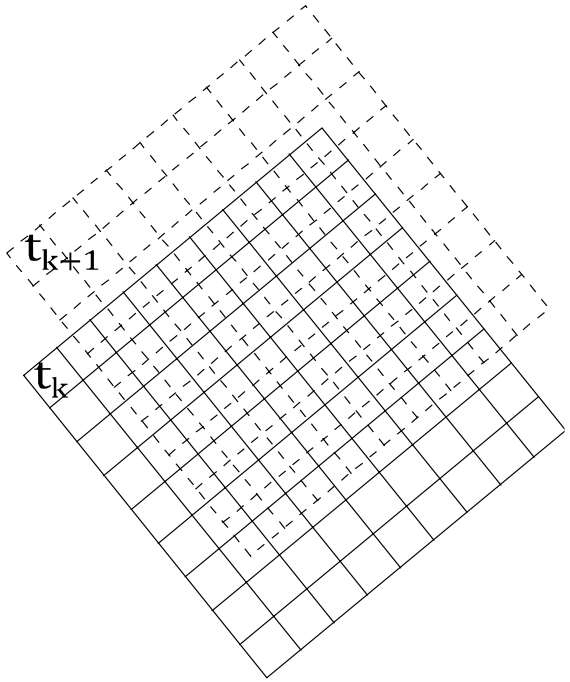
- Autonomous agent P in $\mathrm{v}(x, t; \omega)$
- Travel from x_0 to x_f
- Compute optimal policy that
  - minimizes expected travel time from x_0 to x_f
  - dynamically update it.
- Requires
  - in-mission measurement of $\mathrm{v}(x, t; \omega)$
  - data assimilation to get posterior field.
- Need to update policy based on assimilated field
- Hence, the necessity to use DDDAS[1,2] paradigm
- Earlier work on path planning using DDDAS[3,4]

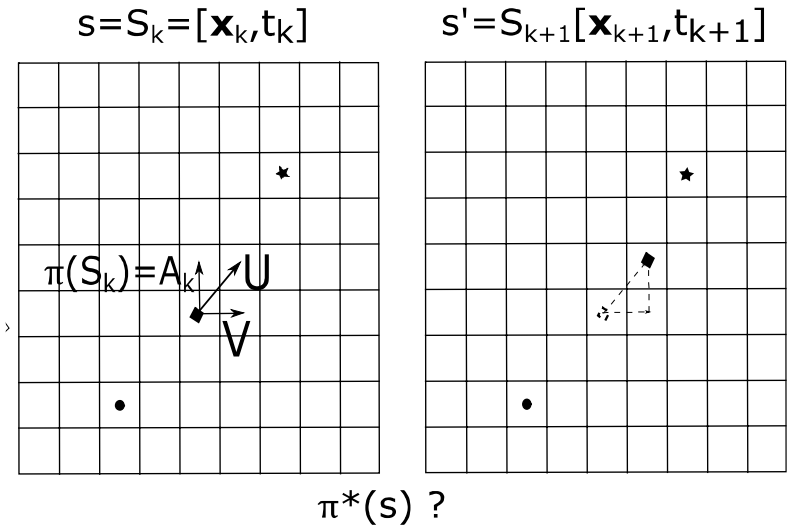


[1] Darema, F.: Dynamic data driven applications systems: A new paradigm for application simulations and measurements. In: International Conference on Computational Science. pp. 662–669. Springer (2004)
[2] Blasch, E., Bernstein, D., Rangaswamy, M.: Introduction to dynamic data driven applications systems. In: Handbook of Dynamic Data Driven Applications Systems, pp. 1–25. Springer (2018)
[3] Singh, V. and Willcox, K., Methodology for Path Planning with Dynamic Data-Driven Flight Capability Estimation, AIAA Journal, Vol. 55, No. 8, pp. 2727-2738, 2017.
[4] D. Sacharny and T. C. Henderson, "Optimal Policies in Complex Large-scale UAS Traffic Management," 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS), Taipei, Taiwan, 2019, pp. 352-357

Problem Setup

- Problem posed as a Markov Decision Process (MDP)
- Discretized State Space: 3D spatio-temporal grid.
  - $S_k = [x_k, tk]$
- Discretized Action Space: Discretized heading
  - $A_k = Fcos\theta\hat{\imath} + Fsin\theta\hat{\jmath}$
  - Agent's speed, F is constant.
  - $\theta \in \{0, \delta, 2\delta, \ldots\ 2\Pi - \delta\}$
- One step reward,
  - $R_k = -\Delta t$
  - $t_{k+1} - t_k = \Delta t \quad \forall k$
- Policy $\pi(S_k) = Ak$
- What is the optimal policy, π^*?
  - How to compute it? – Dynamic Programming (DP)
  - Computationally feasible alternative ?



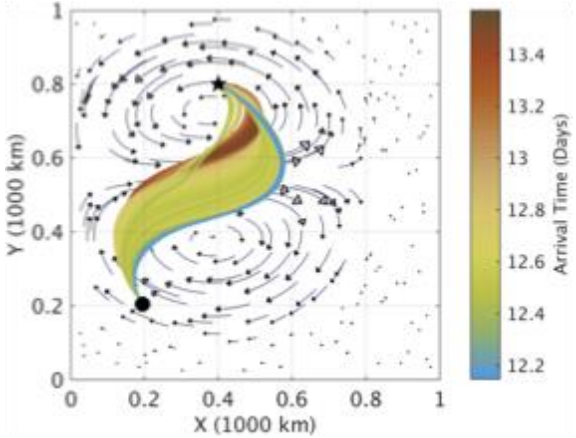


Modelling Framework

Data-Driven Probabilistic Environment Modelling

Environment Forecast: Dynamically Orthogonal (DO) barotropic Quasi-Geostrophic (QG) stochastic equations

Get N realizations of the stochastic velocity field



Stochastic PDEs for Exact Time-Optimal Path Planning

Compute reachability fronts using Hamilton-Jacobi (HJ) level-set S-PDE

For each ω calculate the optimal paths by using the particle back-tracking equation

Obtain distribution of exact time-optimal paths for every ω

HJ S-PDE

$$\frac{\partial \phi(x,t;\omega)}{\partial t} + F(t)\,|\nabla \phi(x,t;\omega)| + v(x,t;\omega).\nabla \phi(x,t;\omega) = 0\,,$$

$$IC:\ \phi(x,0;\omega) = |x - x_0|$$

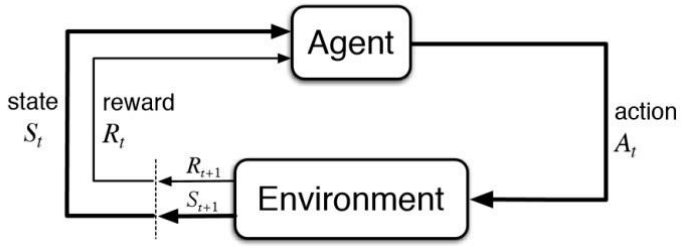
Reinforcement Learning (RL)

$q_\pi(s,a) = \mathbb{E}_\pi[\sum R_k\,|s,a]$

$q_*(s,a) = \mathbb{E}[R(s,a) + \gamma\, max_{a'}\{\, q_*(s',a')\}|s,a]$ Bellman Optimality

DP: Needs model, computationally expensive. Used as a benchmark for performance.

RL: Collect data $(S_k = s, A_k = a, R_{k+1} = r, S_{k+1} = s')$. Estimate q_* .Learning Q-values



Physics-driven Model-based Q-Learning

Phase 1: Transfer Learning (offline)

Compute N rzns of Velocity Field using DO stochastic eqns.

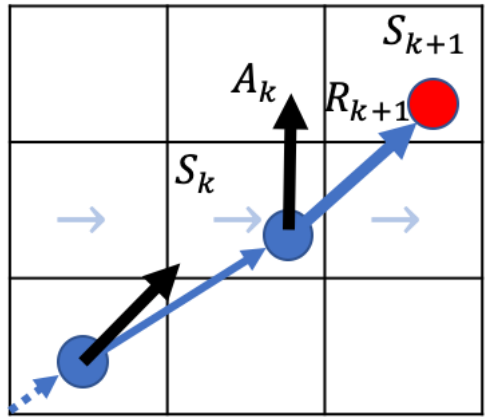
Compute exact time-optimal paths from HJ-PDE & backtracking eqns.

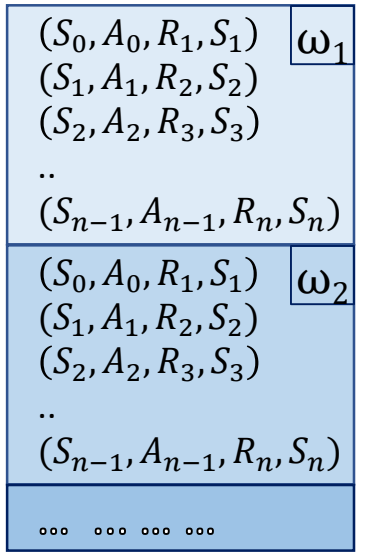
Agent performs action sequence $\{A_k\}$ to follow exact-time optimal path

Build experience buffer by storing tuples $(S_k, A_k, R_{k+1}, S_{k+1})$

Update Q-values using experience buffer

Compute initial policy π^1 from Q-values





Experience Buffer

Phase 2: Dynamic Data Driven Policy Update (in mission)

Perform action according to π^1

Collect mission env. data and compute posterior forecast

Perform future "rollout-simulation" using ε-greedy Q-Learning

Perform next action based on updated Q-values

Q-Learning Update Eqn:

$$Q(S_k, A_k) \leftarrow Q(S_k, A_k) + \alpha\left[R_{k+1} + \max_a Q(S_{k+1}, a) - Q(S_k, A_k)\right]$$

Compute Policy:

$$\pi^1(s) = \max_a Q(s, a)$$

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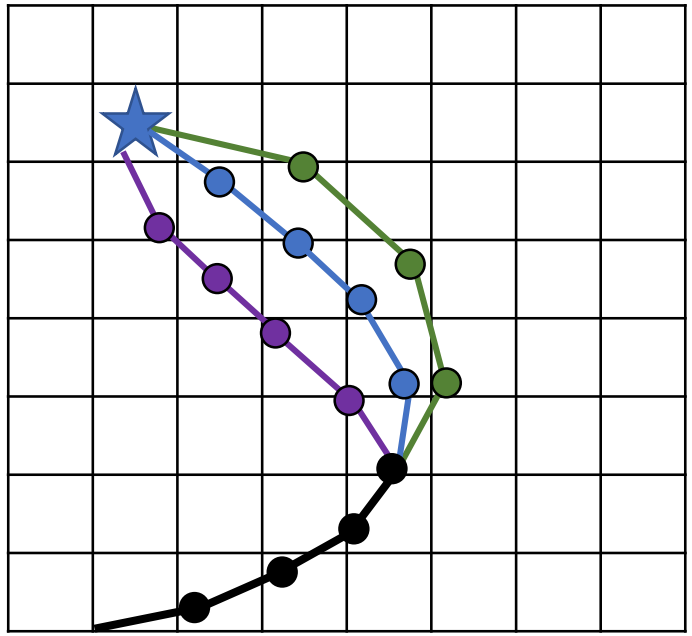
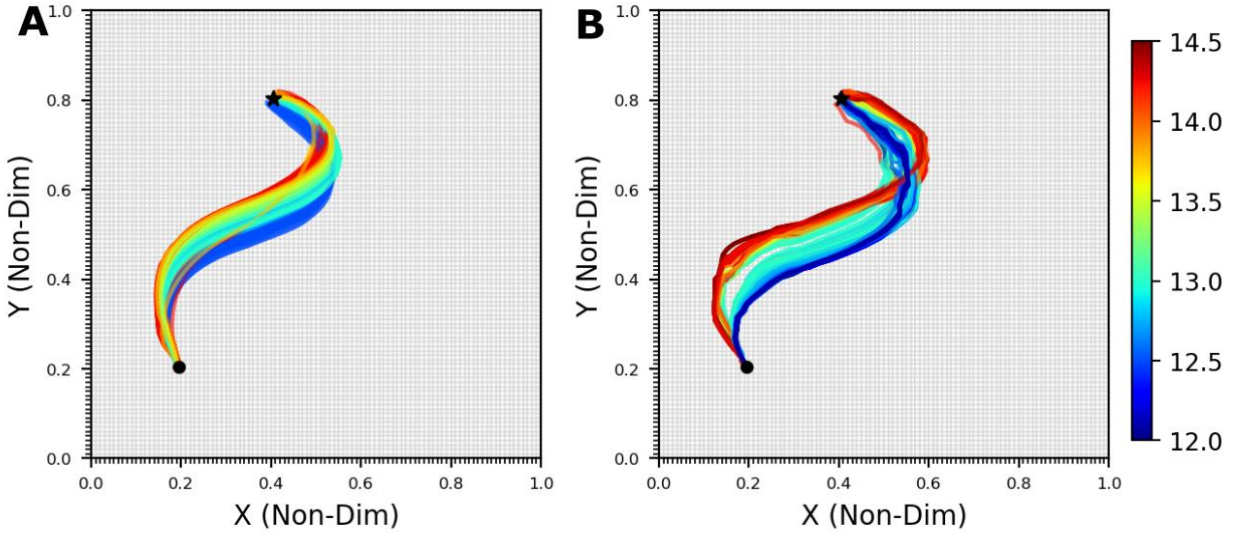


Application

Canonical stochastic Quasi-Geostrophic Double Gyre flow scenario[5]

Problem parameters:

- Square Domain: $1000km \times 1000km$
- Grid Size: $100 \times 100 \times 60$
- $\Delta x = \Delta y = 10km$
- $\Delta t = 0.24\ days$
- Vehicle Speed = $40\ cm/s$
- Action Space: $\{0, 22.5, 45, \ldots 337.5\}$
- No. of realizations, $N = 5000$
  - 4000 for learning initial policy in Phase 1
  - 1000 for testing the algorithm



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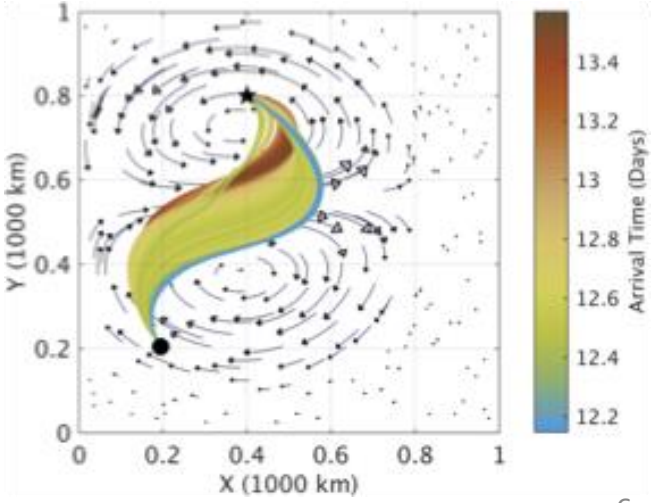
	QL	DP
E[T]	13.1 days	12.6 days
p(fail)	0.46	0.43
Comp. Time	11.4 mins	90 mins



[5] Subramani, D.N., Wei, Q.J., Lermusiaux, P.F.J.: Stochastic time-optimal path-planning in uncertain, strong, and dynamic flows. CMAME 333, 218–237 (2018)

Conclusion and Future Work

- Novel, computationally efficient algorithm to learn a near time-optimal policy.
- Phase 1: Transfer Learning
  - Learn initial policy with Q-Learning update equation from a distribution of exact paths from HJ-PDE in an environment modelled with DO eqns.
- Phase 2: Dynamic Data Driven Policy Update
  - Update policy in-mission using DDDAS principle.
  - Perform data assimilation and future rollout Q-learning simulations.

Next Steps:

- Improvement in data assimilation scheme.
- Evaluation of proposed algorithm in other realistic environments.