

Autonomous 3D Exploration in Large-Scale Environments with Dynamic Obstacles

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1 Introduction

Exploration in dynamic and uncertain real-world environments is an open problem in robotics and it constitutes a foundational capability of autonomous systems operating in most of the real-world. While 3D exploration planning has been extensively studied, the environments are assumed static or only reactive collision avoidance is carried out. We propose a novel approach to not only avoid dynamic obstacles but also include them in the plan itself, to deliberately exploit the dynamic environment in the agent's favor. The proposed planner, Dynamic Autonomous Exploration Planner (**DAEP**), extends AEP [1] to explicitly plan with respect to dynamic obstacles. Furthermore, addressing prior errors within AEP in DAEP has resulted in enhanced exploration within static environments. To thoroughly evaluate exploration planners in dynamic settings, we propose a new enhanced benchmark suite with several dynamic environments, including large-scale outdoor environments. DAEP outperforms state-of-the-art planners in dynamic and large-scale environments and is shown to be more effective at both exploration and collision avoidance.

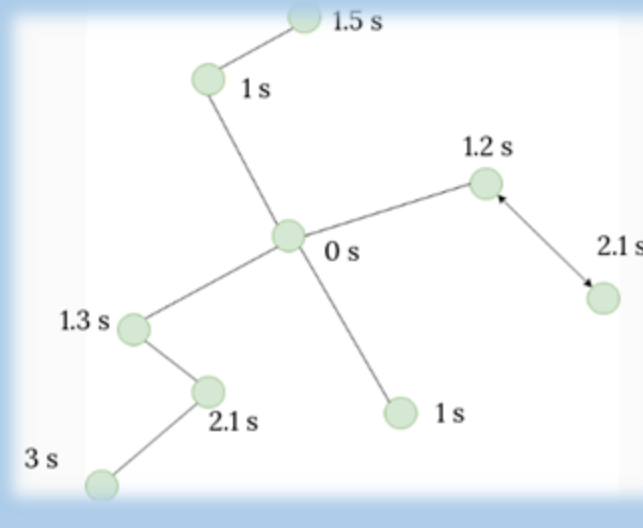
2a Kalman Filter

To estimate the future position of dynamic obstacles has a predictor component been added. Here, a Kalman Filter with a constant velocity model has been employed which contributes with a future trajectory and bounded covariance [3].



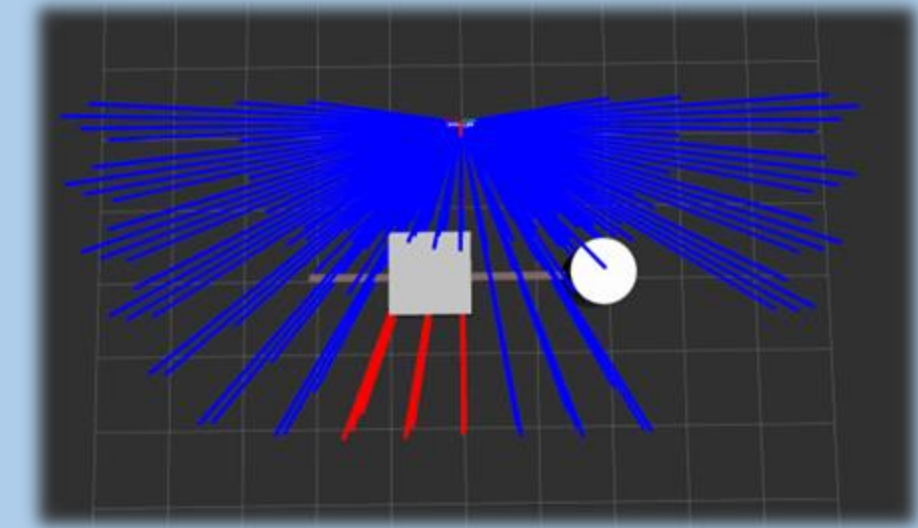
2b Temporal RRT

To incorporate time in the planning process has a Temporal RRT been added, where each node contains the time-of-arrival for the agent. This facilitates temporal planning.



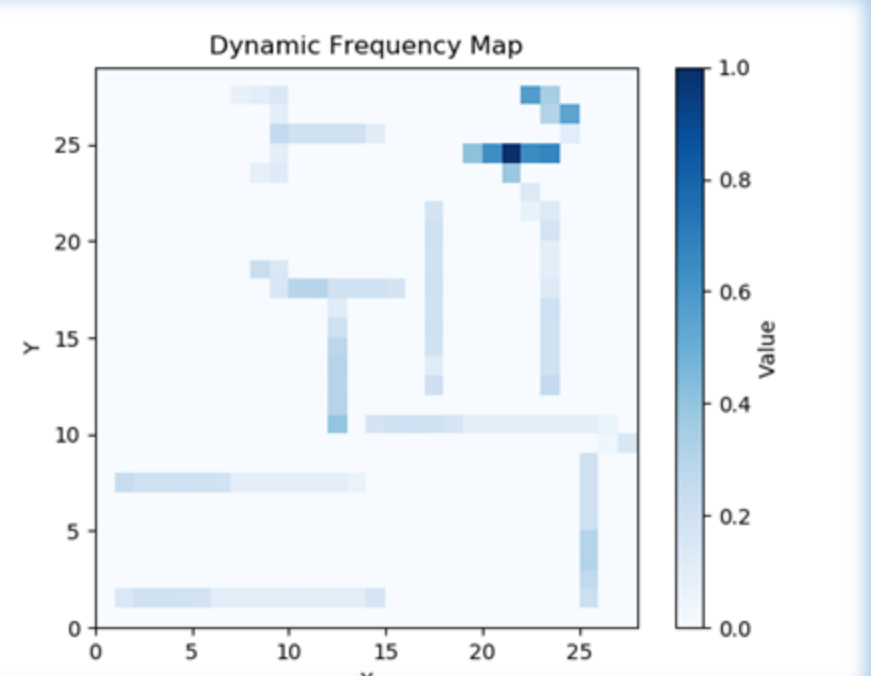
2c Dynamic Gain

Previously, the static information gain has been used to estimate how much **new** information can be acquired from a certain pose. This is no longer feasible since the environment is dynamic. To handle this has Dynamic Gain been added to estimate how much new information can be acquired from a certain pose **at a certain time**.



2d DFM

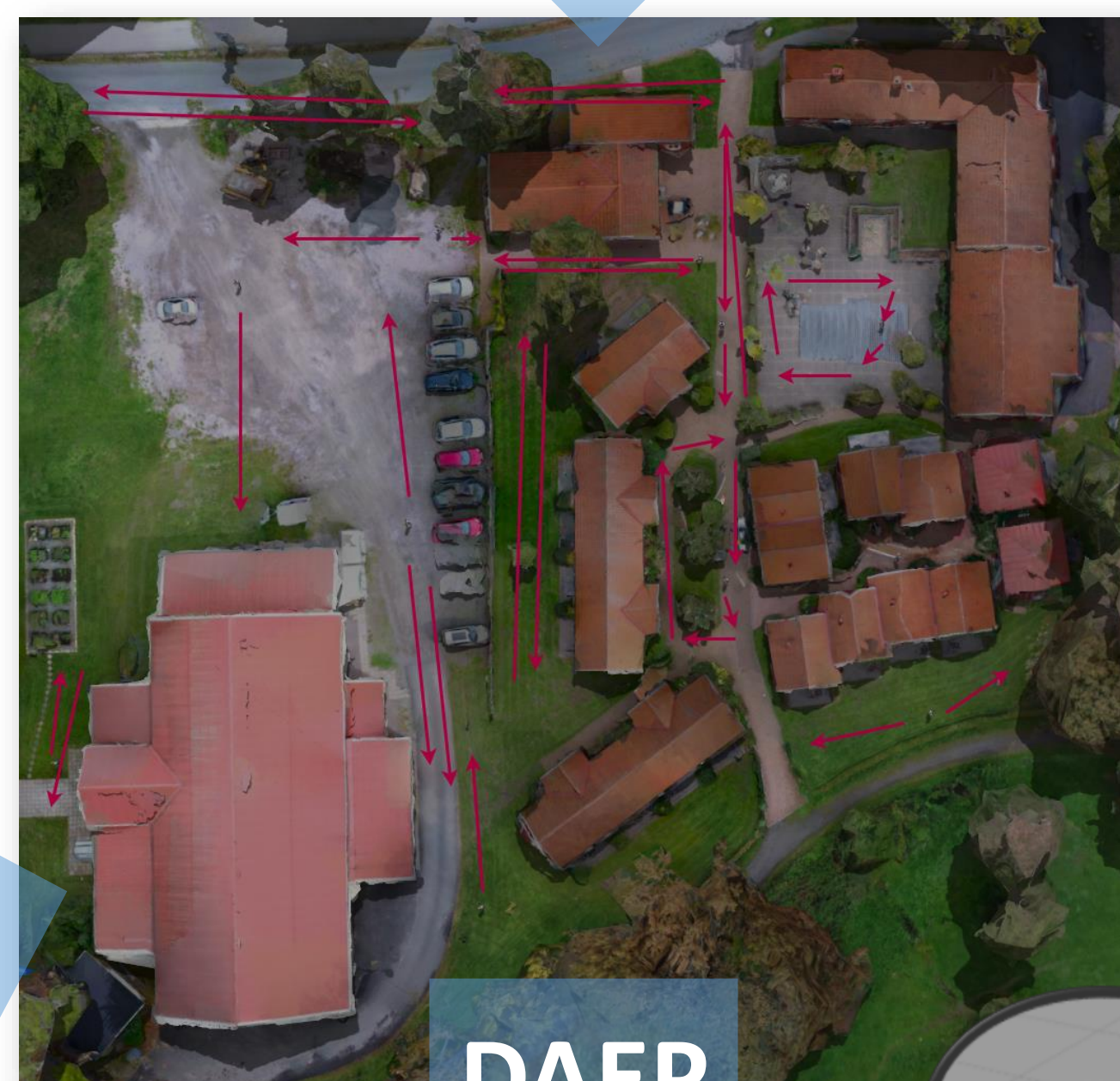
Also, historical data of dynamic obstacle positions is utilized to prioritize certain areas that has historically been occupied but is currently free. This data is represented in a **Dynamic Frequency Map (DFM)**.



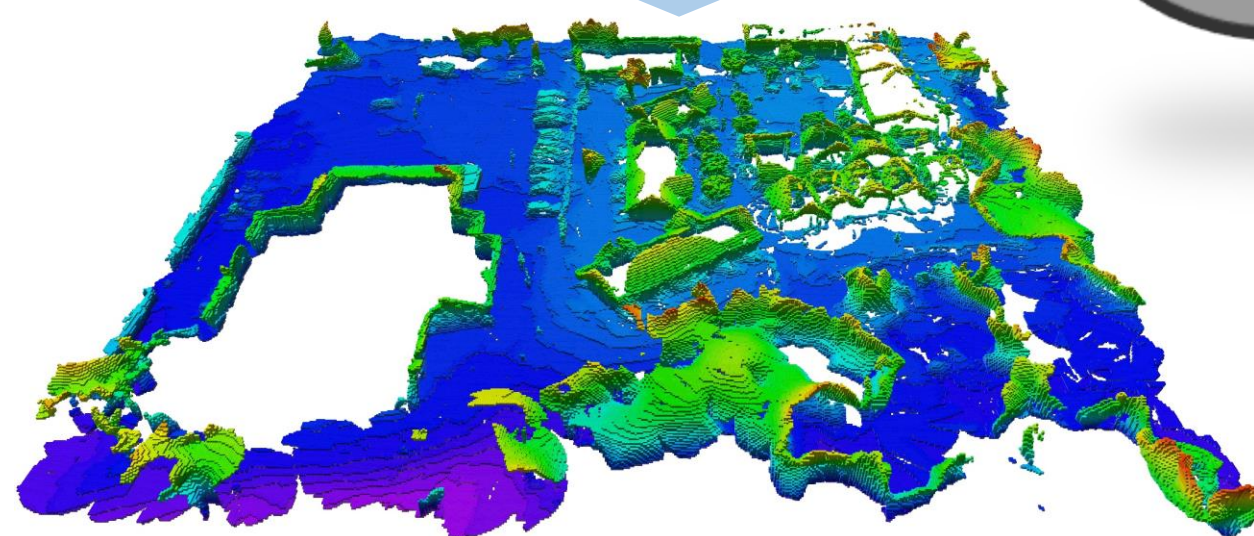
2e Dynamic Score

$$s(\mathbf{p}, t) = d(\mathbf{p}, t) \cdot e^{-\lambda \cdot c(\mathbf{p})} \cdot (1 + (\zeta \cdot DFM(\mathbf{p})))$$

Putting **2a-2d** together, we get the dynamic score function $s(\mathbf{p}, t)$. This function gives a score to each node in the RRT and is used to guide the agent in the dynamic environment. Here we incorporate time, the dynamic gain and the Dynamic Frequency Map to avoid sub-optimal viewpoints.



DAEP

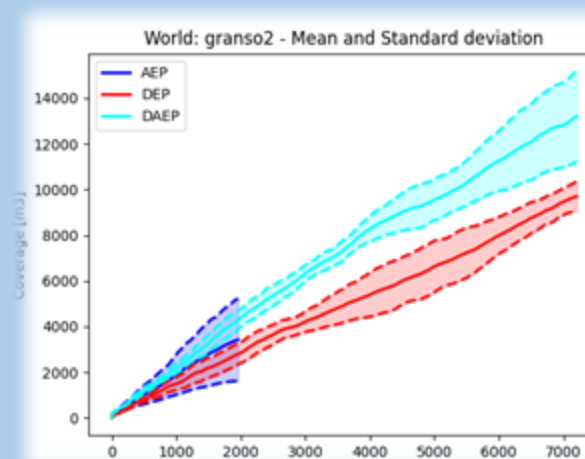
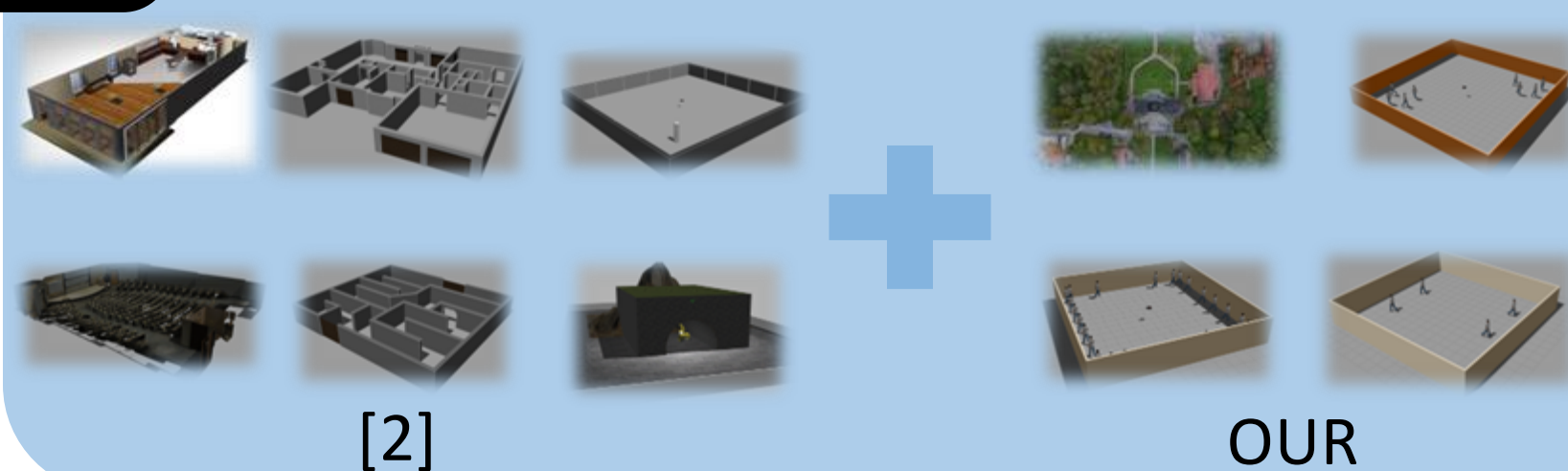


VIDEO

BENCHMARK



3 Evaluation



We evaluate the proposed method in a new benchmark suite which contains 10 worlds, 6 from [2] that has been improved and 4 from us, filled with dynamic obstacles. We show that the proposed method outperforms state-of-the-art exploration planners in both static and dynamic environments. DAEP is also shown to scale well to large-scale environments, while exploring more effectively and safely.