Online Informative Path Planning for Active Classification Using UAVs

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Abstract—In this paper, we introduce an informative path planning (IPP) framework for active classification using unmanned aerial vehicles (UAVs). Our algorithm uses a combination of global viewpoint selection and evolutionary optimization to refine the planned trajectory in continuous 3D space while satisfying dynamic constraints. Our approach is evaluated on the application of weed detection for precision agriculture. We model the presence of weeds on farmland using an occupancy grid and generate adaptive plans according to information-theoretic objectives, enabling the UAV to gather data efficiently. We validate our approach in simulation by comparing against existing methods, and study the effects of different planning strategies. Our results show that the proposed algorithm builds maps with over 50% lower entropy compared to traditional “lawnmower” coverage in the same amount of time. We demonstrate the planning scheme on a multirotor platform with different artificial farmland set-ups.

I. INTRODUCTION

Autonomous mobile systems are increasingly being used to collect information about the Earth and its ecosystems [1]. In many applications, including agriculture [2], gas detection [1, 3], and marine biology [4], robots can provide high-resolution data capturing the spatial and temporal dynamics of complex natural processes. Equipped with sensors, such devices are a flexible, cost-efficient alternative to procedures based on manual sampling or static sensor networks [1]. An open challenge, however, is planning paths for efficient data-gathering given constraints on fuel, energy, or time.

In this work, we consider IPP for a UAV in agricultural monitoring. The objective is to survey a farmland using an on-board image-based weed classifier to quickly find precision treatment targets. By supplying crop health data required for targeted intervention, this workflow reduces chemical usage and yield loss, leading to sustainability and economic gain [5]. In imaging, a key trade-off arises because the same point can be observed from different altitudes; thus, the planning unit must account for degrading sensor accuracy with increased altitude and coverage. Moreover, it must plan given limited battery and computational capacities.

We address the problem by proposing a generic IPP framework for active classification in 3D space. We model the presence of weed on farmland using an occupancy grid. We plan paths online through a combination of global viewpoint selection and evolutionary optimization, which refines a continuous robot trajectory while satisfying dynamic constraints. The resulting informative paths abide by continuous paths for maximum informativeness.

The core contributions of this work are:

1) A new IPP algorithm with the following properties:
   • generates dynamically feasible trajectories in continuous space,
   • obeys budget and sensing constraints,
   • uses a height-dependent noise model to capture sensor uncertainty.

2) The use of an evolutionary strategy to optimize continuous paths for maximum informativeness.

3) A performance evaluation of our IPP algorithm in simulation against state-of-the-art planners and a discussion of different planning strategies.

4) Results from fully autonomously executed tests with AR tags as artificial weeds.

Fig. 1: A comparison of our IPP approach (top-left) to a “lawnmower” coverage path (top-right) for an active weed classification task in precision agriculture using an UAV. The pyramid shows the camera footprint. The plot depicts the variations in map entropy over time. By planning adaptively with a probabilistic sensor model, our approach produces a map with 45% lower entropy of the coverage path in the same amount of time (100s).

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II. RELATED WORK

Significant work has been done recently on IPP in robotics and related fields. In general, most information-gain based strategies seek to minimize map uncertainty using objectives derived from Shannon’s entropy [6, 7]. Unlike in distance-based planning, the path is subject to a budget constraint limiting the number of measurements that can be taken. Formally, this problem can be formulated as a partially observable Markov decision process (POMDP) [8], which provides a general framework for uncertain planning. How-

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ever, the complexity of solving high-dimensional POMDP models motivates more efficient solutions.

The NP-hard sensor placement problem [9] addresses selecting most informative measurement sites in a static setting. Discrete IPP algorithms build upon this task by performing combinatorial optimization over a grid [10–12]. The main drawbacks of such representations are their poor scalability and limited resolution. Alternatively, continuous-space planning involves leveraging sampling-based methods [7] or splines [3, 4, 6]. Our approach belongs to this class of methods, as it does not require a predefined graph of viewpoint locations. Instead, similarly to Chorrow et al. [6], we apply global selection to identify promising viewpoints while escaping local minima, and optimization to refine our trajectory in continuous 3D space.

We also distinguish between (i) non-adaptive and (ii) adaptive planning. Non-adaptive approaches explore an environment using sequence of pre-determined actions. Adaptive approaches [13–15] exploit new measurements based on specific interests. Comparably to Low et al. [16], we use a finite look-ahead, allowing us to propagate map changes and plan adaptively.

IPP addressing UAV imaging is a relatively unexplored area. Recently, Vivaldi e t al. [17] proposed a planner using Bayesian Optimization for mapping diseased trees. Like us, they consider continuous-space plans for active classification with a probabilistic sensor providing aerial imagery. However, their strategy is more computationally intensive as it requires interpolation of a pixel-based map. Moreover, the planning algorithm does not allow for variable-altitude flight. The latter issue has been addressed by Sadat et al. [18] in a similar set-up. Their method assumes discrete viewpoints and prior knowledge of target regions, neglecting sensor noise. In contrast, our approach considers a height-dependent sensor model and incrementally replans as data are collected. Furthermore, we use smooth polynomial trajectories which guarantee feasibility under the UAV’s dynamic constraints.

III. PROBLEM STATEMENT

We define the general IPP problem as follows. We seek a continuous path $P$ in the space of all possible paths $\Psi$ for maximum gain in some information-theoretic measure:

$$P^* = \arg \max_{P \in \Psi} \frac{I[\text{MEASURE}(P)]}{\text{TIME}(P)},$$  

s.t. $\text{TIME}(P) \leq B$,            

where $B$ denotes a time budget and $I$ defines the utility function which quantifies the informative objective. The function $\text{MEASURE}(\cdot)$ obtains discrete measurements along the path $P$ and $\text{TIME}(\cdot)$ provides the corresponding travel time. Maximizing the utility $rate$ in Eq. 1 enables comparing the values of paths over different time scales, as opposed to maximizing only the utility itself.

The above formulation uses a generic utility function $I$ to express the expected reduction in the map’s uncertainty. In Section IV, we consider Shannon’s entropy and classification rate as possible informative measures for our application.

IV. BACKGROUND

We begin with brief descriptions of our approaches to parametrization as key concepts underlying our IPP algorithm.

A. Environment and Measurement Models

We represent the environment (a farmland above which the UAV flies) using a 2D occupancy grid $M$ [19], where each cell is associated with a Bernoulli random variable indicating the probability of weed occupancy. For our measurement model, we assume a rectangular footprint for a down-looking camera providing input to a weed classifier. The classifier provides weed occupancy for cells within field of view (FoV) from a UAV configuration $x$. For each observed cell $m_i \in M$ at time $t$, we perform a log-likelihood update given an observation $z$:

$$L(m_i | z_{1:t}, x_{1:t}) = L(m_i | z_{1:t-1}, x_{1:t-1}) + L(m_i | z_t, x_t),$$  

where $L(m_i | z_t, x_t)$ denotes the height-dependent inverse sensor model capturing the weed classifier output.

In our experiments, we use a binary weed classifier labeling observed cells as “weed” (w) or “non-weed” (nw). For each class, we define curves for our sensor model (Fig. 2) accounting for poorer classification with high-altitude, low-resolution images. At low altitudes, our classifier confidence levels match real datasets [20], and we set a maximum operating altitude, beyond which the classifier cannot provide any information. To account for classifier processing times and limit the rate of information gain in Eq. 1, we also set a minimum time between consecutive measurements.

B. Path Parametrization

To create paths abiding by the dynamic constraints of the UAV, we connect viewpoints $x \in \mathcal{X}$ using the method of Richter et al. [21]. As in their work, we express a 12-degree polynomial trajectory in terms of end-point derivatives, allowing for efficient optimization in an unconstrained quadratic program.

V. PATH PLANNING

In this section, we present our IPP framework. The main idea is to create fixed-horizon plans maximizing an informative objective. To do this efficiently, we first select global viewpoints in 3D space and then optimize the continuous path using an evolutionary method. We overview the steps of the algorithm before discussing its key ingredients.
A. Algorithm

We use a fixed-horizon approach to plan adaptively. During the mission, we maintain measurement viewpoints $\mathcal{X}$ within a horizon $H$, which is expressed in the number of points. We alternate plan execution and replanning, stopping when the elapsed time $t$ exceeds a budget $B$. We adopt a two-stage replanning approach consisting of global viewpoint selection (Lines 3-10) and optimization (Line 11). This procedure is described in Alg. 1 and illustrated in Fig. 3. The following sub-sections detail the key steps of Alg. 1.

Algorithm 1 REPLAN_PATH procedure

1: $t \leftarrow 0; \mathcal{X}^9, \mathcal{X}^\dagger \leftarrow \emptyset$ \(\triangleright\) Initialize global and intermediate viewpoints.
2: while $H \geq |\mathcal{X}^9 \cup \mathcal{X}^\dagger|$ do
3: \hspace{1em} if $t/B < \text{RAND}()$ then \(\triangleright\) Select global objective based on time.
4: \hspace{2em} $x^* \leftarrow \text{Select viewpoint in } \mathcal{L}$ using Eq. 3
5: \hspace{1em} else
6: \hspace{2em} $x^* \leftarrow \text{Select viewpoint in } \mathcal{L}$ using Eq. 4
7: \hspace{1em} $\mathcal{M} \leftarrow \text{SIMULATE\_MEASUREMENT}(\mathcal{M}, x^*)$ \(\triangleright\) With ML.
8: \hspace{1em} $t \leftarrow t + \text{TIME}(x^*)$
9: \hspace{1em} $\mathcal{X}^9 \leftarrow \mathcal{X}^9 \cup x^*$
10: \hspace{1em} $\mathcal{X}^\dagger \leftarrow \mathcal{X}^\dagger \cup \text{ADD\_INTERMEDIATE\_POINTS}(x^*)$
11: $\mathcal{X} \leftarrow \mathcal{X}^9 \cup \mathcal{X}^\dagger; \mathcal{X} \leftarrow \text{CMAES}(\mathcal{X}, \mathcal{M})$ \(\triangleright\) Optimize polynomial.

We include an optional time-varying parameter $t/B$ (Line 3) to gradually bias viewpoint selection towards Eq. 4 from Eq. 3, focusing on weed identification over time. We then simulate a maximum likelihood (ML) measurement at $x^*$ (Line 7) and interpolate intermediate measurement viewpoints $\mathcal{X}^\dagger$ (Line 10) to add degrees of freedom to the polynomial path for optimization.

C. Optimization

In the second step (Line 11), we optimize the polynomial path by solving Eq. 1 in Section III using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES). We opt for this method as our discrete measurement model does not provide the continuity necessary for information gradient-based optimization. Moreover, the CMA-ES has been applied successfully for continuous curve fitting in constrained spaces matching our problem set-up [22].

In Section VI, we consider global viewpoint objectives for (i) information gain only (Eq. 3), (ii) classification gain only (Eq. 4), and (iii) using the time-varying parameter (Alg. 1). For the CMA-ES, we consider (i) globally optimizing $\mathcal{X}$ (Fig. 3c) and (ii) optimizing $\mathcal{X}^\dagger$ only (Fig. 3d) for inter-segment refinements. We refer to these two optimization methods as the “global” and “local” CMA-ES, respectively. For the global CMA-ES, the points in $\mathcal{X}^9$ vote on the optimization objective for the entire trajectory.

VI. EXPERIMENTAL RESULTS

In this section, we first evaluate our proposed IPP framework in simulation by comparing it to existing algorithms and study different the variants of our algorithm introduced in Section V. Then, we implement our complete system in an environment with artificial weed distributions.

A. Comparison Against Benchmarks

We validate our framework in simulation on 100 $50 \times 50$ m farmland environments with randomly scattered weeds. To analyze how our algorithm behaves with different weed densities, we generate Poisson distributions with 50 to 250 weeds. We use a resolution of 0.5 m with thresholds of $\delta_{nw} = 0.25$ and $\delta_w = 0.75$ for the occupancy grid map. To simulate false measurements, uniform noise is added based on the same probabilistic distribution as our sensor model (Fig. 2). The number of false positive cells is limited to 800 to avoid excessive noise in non-occupied regions.

Our methods are evaluated against traditional “lawnmower” coverage and the sampling-based rapidly exploring information gathering tree (RIG-tree) introduced by Hollinger and Sukhatme [7], a state-of-the-art IPP algorithm. We specify a 300 s budget $B$. For the weed classifier, we set a 60$^\circ$ camera FoV with a square footprint and maximum measurement frequency of 0.2 Hz. Map entropy, classification rate, and mean F2-score are considered as metrics common for classification tasks. Following a similar approach to Pomerleau et al. [23], the cumulative distribution function (CDF) of entropy is computed over a time histogram to summarize the variability among trajectories. For this
metric, faster-rising curves represent quicker reductions in map uncertainty and thus better performances. We use mean F2-score as the accuracy statistic to emphasize the effects of relatively fewer false negative misclassifications.

The UAV position for both IPP schemes is initialized to the map center with 40 m altitude. The reference velocity and acceleration for trajectory optimization are 3 m/s and 1.5 m/s². For our planner, we use a replanning horizon \( H \) of 5 viewpoints to limit optimization complexity. For RIG-tree, we associate the cost of a vertex (viewpoint) with accumulated travel time, and its information value as map entropy given a new measurement. To compute cost, trajectory optimization is performed for each edge, assuming measurements taken from rest. As the map cells are independent, we apply the modular pruning strategy described in [7].

We provide RIG-tree with prior knowledge from a high-altitude scan for initial planning. Then, we alternate between tree construction and plan execution to allow for adaptivity. Each tree construction is terminated after the same ∼ 20 s allowed for trajectory optimization in our planner.

For the coverage planner, we define a height (14.43 m) and maximum velocity (0.844 m/s) for complete coverage given the specified budget. To provide a fair comparison to the IPP planners, several coverage patterns were evaluated and the best-performing one selected.

Fig. 4 shows how the algorithms score on the metrics during the mission. For our planners, results using the time-varying objective (as in Alg. 1) are included since we found it to be the most effective global viewpoint selection strategy. As expected, entropy reduction rates (left) are constant with naïve coverage (green) as the environment is scanned uniformly. In contrast, the IPP methods perform better as they permit variable-altitude flight for wider FoVs. As shown in Fig. 1, our planners usually produce paths resembling spirals, starting with descent to the unknown map center. Such motions permit the collection of low-quality, high-altitude data before focusing on map corners and detected areas of interest.

The F2-score variations (right) suggest that coverage planning yields most accurate classification in the observed areas. This likely occurs due to the low flight altitude permitted by the allocated budget, basing noise additions on relatively certain regions of the sensor curves. We note that this metric does not account for the fact that, early in the mission, a large section of the map is completely unknown (Fig. 1).

Our planners (red, yellow) produce more informative paths than RIG-tree (purple) given the same planning time. This indicates that our strategy finds promising viewpoints in 3D space more efficiently than incremental sampling-based techniques. Moreover, it does not require prior knowledge for initialization and generates smooth trajectories.

For our planners, we observe that the global CMA-ES optimizer (yellow) produces both higher gains in entropy and classification rate compared to local optimization of intermediate points only (red). The following sub-section offers a more detailed comparison.

B. Evaluation of Planning Strategies

Next, we study changing planning strategies in our framework for the same simulation set-up to assess their effects. In our experiments, we consider varying:

- **Global viewpoint objectives:** information only (Eq. 3), classification only (Eq. 4), using time-varying parameter (Alg. 1)
- **Optimization methods:** no CMA-ES, local CMA-ES (Fig. 3d), global CMA-ES (Fig. 3c)

Fig. 5 compares the global viewpoint selection objectives with the global CMA-ES. The curves illustrate the coverage-resolution trade-off: for the classification objective (light blue), flying at low altitudes quickly produces a map with cells within occupancy thresholds, as shown by the sharpest rise in classification rate (center). However, entropy reduction (left) is limited and initial accuracy (right) is poor since improving confidence on “weed” and “nonweed” labels is not accounted for. By considering elapsed time when selecting global viewpoints (black), we balance between improving existing information quality and exploring unknown areas to obtain a high certainty map with efficient classification.

Fig. 6 compares the CMA-ES optimization methods for the classification global viewpoint selection objective. Optimizing the entire trajectory using the global CMA-ES (yellow) leads to best performance on all three metrics, likely due to the highest number of optimized variables. This highlights the effectiveness of using greedy selection to initialize an evolutionary-based trajectory optimizer, even in noisy conditions. In contrast, applying local optimization (red) on the short replanning horizon lead to minor improvements.

C. Experiments

We show our IPP strategy running in real-time on an As-cTec Pelican UAV platform. The experiments are conducted in an empty 4 × 4 m indoor environment with a maximum altitude of 3 m, and state estimation provided by the Vicon.
In this work, we targeted the problem of planning informative paths for active classification. We presented an adaptive strategy that generates dynamically feasible paths in continuous 3D space for information-theoretic objectives.

1This experiment can be seen in the video attachment.
The approach was validated with one of the most important applications for precision agriculture, weed detection. An evaluation in simulation showed its advantages over a “lawn-mower” coverage pattern and sampling-based IPP algorithm in terms of informative metrics. We also demonstrated the effects of planning with different objectives and optimization strategies. Our experiments showed the framework running both in simulation and on a real multicopter platform.

Future work will target full field deployments with a real weed classifier. Interesting research directions involve considering different environment sizes and incorporating prior knowledge from previous scans.

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