Energy-Aware Dynamic Mission Planning Algorithm for UAVs

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***Abstract*— abstract abstract abstract abstract abstract abstract abstract abstract abstract abstract abstract abstract abstract abstract**

I. Introduction

Planning a mission for unmanned aerial vehicles (UAVs) operating outdoors is a challenging task. Scenarios such as precision agriculture, search and rescue, and surveillance require advanced levels of autonomy along with strictly limited energy budgets–with the typical instance being a UAV used to inform its grounded counterparts of patterns detected while flying. Currently, UAVs flying outdoors are often semi-autonomous, in the sense that the mission is static and usually defined using a mission planning software [1]. Such a state of practice has prompted us to propose an *energy-aware dynamic mission planning algorithm* for UAVs. The algorithm attempts to combine and generalize some of the past body of knowledge on the mobile robot planning problem, and highlights the increasing *computational demands* and their relation to energy consumption, path, and autonomy.

Planning algorithms for mobile robots broadly are not a new concept, in that they are correlated to such topics as trajectory generation and path planning. Generally, these algorithms select an energy-optimized trajectory [2], by e.g., maximizing the operational time [3], but in practice apply to few robots [4], and focus on optimizing motion control for these robots [5], despite compelling evidence for the systems' energy being influenced by the computations over bare motion [6]. For UAVs specifically, rotorcrafts have equally gained research interest in terms of algorithms for energy-optimized trajectory generation [7], [8]. Furthermore, past mission planning algorithms–which include a broader concept of a mission being a set of tasks along with a motion plan–also focus on the trajectory [6], [9], and apply to few robots [10], [11]. Yet, computations of such systems are only expected to increase in the near future.

The proposed algorithm alters the energy consumption dynamically by means of mission-specific parameters: the Quality of Service (QoS) of the computations, and the trajectory-explicit equations (TEEs) adjustments. In the remainder of the paper, we strictly adopt the following notation. We refer to the values of mission-specific QoS and TEEs parameters as computations and adjustments, to the constraints sets that delimit such computations and adjustments as QoS and TEEs sets, and to the current trajectory as TEE. Our goal is a mission extension by optimizing both computations and adjustments as the UAV flies and its batteries drain. First, the algorithm optimizes computations requiring the UAV to include robot operating system (ROS) nodes. Then, it optimizes adjustments–a way to alter the trajectory–and guides the UAV using a vector field [12] that converges smoothly to such trajectory. It relies on the assumptions of the mission being *periodic* and *uncertain*. The periodicity is directly observed, by e.g., the UAV flying in repetitive patterns, and the uncertainty accounts for the environmental interference with e.g., a fixed-wing UAV drifting due to windy weather. It addresses the periodicity modeling the energy with Fourier analysis–being the mission periodic, we expect the energy to evolve also periodically–and the uncertainty with a state estimator. It selects the controls (computations and adjustments) using robust output feedback model predictive control (MPC).

In the spirit of reducing waste, costs, and resources, we showcase the algorithm using the problem of dynamic mission planning for a precision agriculture fixed-wing UAV. Such a scenario is often put into practice [13] with ground mobile robots used for harvesting [14]–[19], and UAVs for preventing damage and ensuring better crop quality [1], [20]. The mission consist of a UAV flying in ellipses shifted in time, detecting obstacles using a convolutional neural network (CNN), and informing grounded mobile robots employed for future harvesting–a monitoring mission optimized for the craft's dynamics. The algorithm plans the mission controlling the processing rate and the length of the semi-major and -minor axis. Data indicates a potential extension of up to 13 minutes over an hour by merely switching to the lowest computations.

The remainder of the paper is organized as follows. The overview of dynamic mission planning is set in Section II, along with a suitable model for the position and energy. The algorithm that uses the model and solves the mobile

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robot dynamic mission planning problem is proposed in Section III. Section IV presents the result and showcase the performance. The paper finishes with some conclusions in Section V.

II. Mission Planning Overview

Let the mission be a generic continuous twice differentiable TEE φ and a set of σ tasks $\psi_1, \ldots, \psi_\sigma$. Moreover, let t_f be the mission final time, $[\,\cdot\,]$ the set $\{1, 2, \ldots, \cdot\}$, and $\underline{\cdot}, \overline{\cdot}$ the upper and lower bound of $\,\cdot\,$.

Definition II.1 (Mission)**.** At a time instant $k \in [0, t_f) \subseteq \mathbb{R}_{\geq 0}$, the mission is defined as the ordered list

$$\mathcal{M}_k := \{(\varphi, \psi_1, ..., \psi_\sigma) \mid \exists\ \varphi \in \mathbb{C}_k, \\ \psi_i \in \mathbb{S}_{k,i}\, \forall i \in [\sigma]\}, \tag{1}$$

where $\mathbb{C}_k := [\underline{c}_k, \overline{c}_k] \subseteq \mathbb{R}$ is the TEEs set, and $\mathbb{S}_{k,i} := [\underline{s}_{k,i}, \overline{s}_{k,i}] \subseteq \mathbb{Z}_{\geq 0}$ the i-th task QoS set.

The overall plan is the union of all the missions. If for simplicity the system is sampled discrete-time

$$\mathcal{M} := \bigcup_{i \in [t_f]} \mathcal{M}_i, \tag{2}$$

the algorithm inputs $\mathcal{M}$ and outputs the position, the instantaneous energy consumption, and the controls sequence–an action performed evolving the mission state.

A. Mission state

The mission state is the UAV's position in space and the energy evolution in time. Despite we show a linear relation between the instantaneous energy and the energy evolution, the two are different. We show after the main results how such approach indeed allowed us variability in terms of the systems behaving periodically, piece-wise periodically, or merely linearly with sporadic periodicity.

Consider the position $\mathbf{p} \in \mathbb{R}^2$ of a UAV flying at an assigned altitude $h \in \mathbb{R}_{>0}$ w.r.t. some inertial navigation frame $\mathcal{O}_W$, the set

$$\mathcal{P}_k := \{\mathbf{p}_k \mid \varphi_k(\mathbf{p}_k, c_{k,1}, \ldots, c_{k,\rho}) \in \mathbb{C}_k\}, \tag{3}$$

delimits the area where the k-th TEE $\varphi_k : \mathbb{R}^2 \times \mathbb{R}^\rho \to \mathbb{R}$ is free to evolve using ρ adjustments $\mathbf{c}_k := c_{k,1}, ..., c_{k,\rho}$, being the TEE satisfied for all the approaching points $\varphi_k \to \mathbb{C}_k$.

The algorithm uses the concept to select the adjustments s.t. $\varphi_k(\mathbf{p}_k, \mathbf{c}_k^0)$ has the highest energy value. It guides the UAV to the new position $\mathbf{p}_{k+1}$ using the vector field of $\mathit{\Phi} := \varphi_k(\mathbf{p}_k, \mathbf{c}_k^0)$, deriving the direction to follow–the desired velocity vector

$$\dot{\mathbf{p}}_d(\mathbf{p}_k) := E\nabla\mathit{\Phi} - k_e \mathit{\Phi}\nabla\mathit{\Phi}, \;\; E = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}, \tag{4}$$

where $\nabla\mathit{\Phi} \in \mathbb{R}^2$ is the gradient, E specifies the tracking direction, and $k_e \in \mathbb{R}_{\geq 0}$ the gain to adjusts the speed of convergence. The direction the velocity vector $\dot{\mathbf{p}}_d$ is pointing at is generally different from the course heading due to the atmospheric interference.

The algorithm models the energy using a state $\mathbf{q} \in \mathbb{R}^j$ derived from Fourier analysis (the meaning of j is clarified to the reader shortly) and decompose such evolution in the energy due to the trajectory, and computations–an approach adapted from our earlier work on computational energy analysis [21], [22], and energy estimation of a fixed-wing UAV [23].

B. Energy evolution due to trajectory

Let us consider a Fourier series $h : \mathbb{R}_{\geq 0} \to \mathbb{R}$ of an arbitrary order $r \in \mathbb{Z}_{\geq 0}$ for the purpose of energy modeling of the mission

$$h(t) = \sum_{n=0}^{r} a_n \cos\frac{nt}{\xi} + b_n \sin\frac{nt}{\xi}, \tag{5}$$

where $\xi \in \mathbb{R}$ is the characteristic time, and $a_n, b_n \in \mathbb{R}$ the Fourier series coefficients.

Suppose uncertainty in the form of $\mathbf{w}_k \in \mathbb{R}^j, v_k \in \mathbb{R}$ accounting for the unknown state and output is not present. The non-linear model in Equation (5) can be expressed using an equivalent linear discrete time-invariant state-space model

$$\begin{cases} \mathbf{q}_{k+1} &= A\mathbf{q}_k + B\mathbf{u}_k + \mathbf{w}_k \\ y_k &= C\mathbf{q}_k + v_k \end{cases}, \tag{6}$$

where $y_k \in \mathbb{R}_{\geq 0}$ is the instantaneous energy consumption. We prove formally in the Theorem III.1 the instantaneous energy being obtained as a linear combination of the state. The state $\mathbf{q}$ mimics the original Fourier series coefficients

$$\begin{aligned} \mathbf{q}_k &= \begin{bmatrix} \alpha_0 & \alpha_1 & \beta_1 & \cdots & \alpha_r & \beta_r \end{bmatrix}^T, \\ A &= \begin{bmatrix} 1 & & & \\ & A_1 & & \\ & & \ddots & \\ & & & A_r \end{bmatrix}, \; A_n = \begin{bmatrix} 0 & \frac{n}{\xi} \\ -\frac{n^2}{\xi^2} & 0 \end{bmatrix}, \\ C &= \begin{bmatrix} 1 & 1 & 0 & \cdots & 1 & 0 \end{bmatrix}, \end{aligned} \tag{7}$$

where $\mathbf{q}_k \in \mathbb{R}^j$ given $j := 2r+1$, $A \in \mathbb{R}^{j \times j}$ is the state transmission matrix, and $C \in \mathbb{R}^j$ is the output matrix. In matrix A, the first value is one, A_n is later on the diagonal, and zero in the remainder.

The control $\mathbf{u}$ along with the input matrix

$$\begin{aligned} \mathbf{u}_k &= \begin{bmatrix} g(\mathbf{s}_k) - g(\mathbf{s}_{k-1}) & \mathbf{c}_k - \mathbf{c}_{k-1} \end{bmatrix}^T, \\ B &= \begin{bmatrix} 1 & \omega_{k,1} & \cdots & \omega_{k,\rho} \\ & 0 & & \\ & & \ddots & \\ & & & 0 \end{bmatrix}, \end{aligned} \tag{8}$$

where $\mathbf{s}_k$ is defined in Subsection II-C, $\mathbf{u}_k \in \mathbb{R}^l$ is the control given $l := 1+\rho$, $\mathbf{u}_1 = \begin{bmatrix} 0 & \cdots & 0 \end{bmatrix}^T$ and $B \in \mathbb{R}^{j \times l}$. Moreover, the first item is one, while the others on the first row are gain factors $\omega_k \in \mathbb{R}$, quantifying the contribution of a given adjustment to the instantaneous energy.

The energy evolution analysis necessitates the following realistic assumption.

Assumption II.1 (Energy evelution periodicity)**.** Given two time instants $k_1, k_2 \in [t_f]$ s.t. $k_1 > k_2$ and a constant value $n \in \mathbb{R}_{>0}$, there exist an arbitrary constant displacement $e \in \mathbb{R}$

$$|y_k - y_{k+n}| = e \ \forall k \in [k_1, k_2]. \tag{9}$$

Physically, the time evolution of the instantaneous energy consumption is assumed periodic, in the sense that it presents repetitive patterns. We show in Section IV the assumption being eased in practice to a set $\mathbb{E} \subset \mathbb{R}$, or omitted under specific conditions.

Equation (8) accounts for the energy due to the computations. The energy due to the adjustments is merely a linear combination of the gain factor and the adjustment. Nevertheless, the change updates the path which will hence affect the reading from the sensors and adjust the energy evolution accordingly. The linearity simulates how a variation affects the energy, for instance, a decrement in the adjustment radius of a circle when the TEE is a circle, adds a negative contribution, thus simulates the lowering of instantaneous energy consumption.

In the case of the system behaving ideally (i.e., with no uncertainty), we expect a state (energy evolution) evolving accordingly to its output (instantaneous energy consumption). Such observation is summarized in the following Lemma.

Lemma II.2 (State, output proportionality)**.** Suppose the system of Equation (6) evolves with no uncertainty ($\mathbf{w} = \mathbf{0}, v = 0$) and Assumption II.1 holds. Given two time instants $k_1, k_2 \in [t_f]$

$$\|\mathbf{q}_{k_1}\| \geq \|\mathbf{q}_{k_2}\| \iff y_{k_1} \geq y_{k_2}. \tag{10}$$

Proof. "*The easy proof is trivial and is left as an exercise to the reader :P*"

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C. Energy evolution due to computations

The energy cost of the computations is assessed using `powprofiler`, an open-source modeling tool presented in our previous work [21], that measures software configurations empirically and builds an energy model. Specifically, the tool builds a linear interpolation, one per each task. It requires the user to implement the mission as a ROS system with one or more ROS nodes changing the computational load by node-specific ROS parameters. A way to simulate the change of the computations.

The plan $\mathcal{M}$ contains a set of ordered lists with σ tasks each (recall Definition II.1). These tasks are simulated by σ ROS nodes $\Psi(\mathbf{s}_k) := (\psi_1(s_{k,1}), \ldots, \psi_\sigma(s_{k,\sigma}))$, in fact they input the desired and output the actual computations. Let us define the computations

$$\mathbf{s}_k := \{s_{k,1}, \ldots, s_{k,\sigma} \mid \psi_i(s_{k,i}) \in \mathbb{S}_k \, \forall i \in [\sigma]\}, \tag{11}$$

where $s_{k,i} : \mathbb{Z}_{\geq 0} \to \mathbb{Z}_{\geq 0}$ returns the i-th computation, $\mathbf{s}_k \in \mathbb{S}_k \subseteq \mathbb{Z}^\sigma_{\geq 0}$ the set of σ computations at time k being $\mathbb{S}_k := \bigcup_{i \in [\sigma]} \mathbb{S}_{k,i}$.

Let us further define $g : \mathbb{Z}_{\geq 0} \times \mathbb{Z}_{\geq 0} \to \mathbb{R}_{\geq 0}$ as the instantaneous energy value obtained interrogating `powprofiler`. The instantaneous computational energy component can be defined

$$y^c_k := g\left(\mathrm{QoS}_{k,0}, \ldots, \mathrm{QoS}_{k,\sigma-1}\right) = g\left(\mathbf{s}_k\right). \tag{12}$$

III. Algorithm

Given an initial mission $\mathcal{M}_1$ (TEE φ_1, tasks Ψ, computations $\mathbf{s}_1 \in \mathbb{S}_1$, and adaptations $\mathbf{c}_1 \in \mathbb{C}_1$), the algorithm produce a valid mission evolution.

Definition III.1 (Valid mission evolution)**.** At a generic time instant $k \in [t_f]$ a mission evolution $\mathcal{M}_k$ is valid

$$\begin{aligned} \mathbf{u}^a_k = \{(\mathbf{c}_k, \mathbf{s}_k) \, |(\varphi(\mathbf{p}_{k-1}, \mathbf{c}_{k-1}), \Psi(\mathbf{s_{k-1}})) \in \mathcal{M}_{k-1} \\ \implies (\varphi(\mathbf{p}_k, \mathbf{c}_k), \Psi(\mathbf{s}_k)) \in \mathcal{M}_k\}. \end{aligned} \tag{13}$$

Note that the position evolution can be computed directly from Equation (4). If the velocity is $v \in \mathbb{R}_{\geq 0}$, and starting point $\mathbf{p}_0$, $\mathbf{p}_{k+1} = \mathbf{p}_k \dot{\mathbf{p}}_d(\mathbf{p}_k)/v$.

Let us proof that if the mission evolution is valid, the instantaneous energy consumption is a linear combination of the state from the Equation (6).

Theorem III.1 (State output linearity)**.** Consider the mission from Definition II.1, the valid mission evolution from III.1, and assume Assumption II.1 holds. Likewise in Lemma II.2, the model behaves ideally. Then, the instantaneous energy consumption y_k is a linear combination of the state $\mathbf{q}_k$ and $\mathcal{M}_k$ produce a valid mission evolution $\mathcal{M}_{k+1} \, \forall k \in [t_f - 1]$.

Proof. *

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A. Deployment algorithm

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IV. Evaluation

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V. Conclusion and Future Work

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