Energy-Aware Dynamic Mission Planning Algorithm for UAVs

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I. Introduction

Planning a mission for unmanned aerial vehicles (UAVs) operating in outdoor scenarios such as precision agriculture, search and rescue, and surveillance is a challenging task. It requires 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 that highlights the increasing *computational demands* and their relation to the energy consumption, path, and autonomy.

Planning algorithms for mobile robots broadly are not a new concept and have been extensively studied, 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 a narrow class of robots [4], and focus on optimizing motion control for such robots [5], despite compelling evidence for these 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 the narrow class of robots [10], [11]. Yet, computations of such systems are only expected to increase in the near future. Unlike the past approaches, the algorithm presented here attempts to combine and generalize some of these technical breakthroughs, correlate the extensively studied energy planning to the growing computational demands, and validate its findings using UAVs.

The proposed algorithm alters the energy consumption dynamically by means of mission-specific parameters: the Quality of Service (QoS) of the onboard computations, and the trajectory-explicit equations (TEEs) of the path. Our goal is a mission extension by optimizing both QoS and TEEs as the UAV flies and its batteries drain. The algorithm optimizes QoS requiring the UAV to include robot operating system (ROS) nodes. It optimizes TEEs–an abstraction of the path to follow–and guides the UAV using a vector field that converges smoothly to the path. 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. We propose the Fourier analysis to address the periodicity assumption–being the mission periodic, we expect the energy to evolve also periodically–and a state estimator to cope with the uncertainty assumption. The algorithm selects the controls (QoS and TEEs parameters) using robust output feedback model predictive control (MPC).

To show case the algorithm we consider the problem of dynamic mission planning for a precision agriculture fixed-wing UAV. Precision agriculture is rising in demand for reducing waste, costs, and resources while increasing outputs and utilization [12], with mobile robots being increasingly used for e.g., harvesting [13]–[18]. 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 survey 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. Such a scenario is frequently put into practice, with complex monitoring strategies being often implemented utilizing UAVs for preventing damage and ensuring better crop quality [19]. Data indicates a potential extension of up to 13 minutes over an hour by merely switching to the lowest QoS.

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

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problem is proposed in Section III. Section IV presents a fixed-wing UAV flying in an agricultural scenario showcasing the performance. The paper finishes with some conclusions in Section V.

II. Mission Planning Overview

The mission is a time-varying motion plan and a set of tasks the UAV is supposed to perform along the TEEs and QoS parameters constraints

$$\mathcal{M} := \left\{ \varphi_k,\ (\underline{c}_k, \overline{c}_k), \bigcup_{n=0,\dots,\rho-1} (\underline{\mathrm{QoS}}_{k,n}, \overline{\mathrm{QoS}}_{k,n}) : \forall k \in \mathbb{T} \right\}, \tag{1}$$

where $\mathbb{T} := [0, t_f) \subseteq \mathbb{R}_{\geq 0}$ is the mission time, $t_f \in \mathbb{R}_{\geq 0}$ the final instant, $\varphi_k \in \mathbb{R}$ is a generic continuous twice differentiable TEE along its upper and lower bounds $(\underline{c}_k, \overline{c}_k) \in \mathbb{R}^2$ (the motion plan–an ordered pair), and a set of upper and lower bounds for the σ tasks $(\underline{\mathrm{QoS}}_{k,i}, \overline{\mathrm{QoS}}_{k,i}) \in \mathbb{Z}^2_{\geq 0}$ (a set of also ordered pairs).

The algorithm inputs the mission and outputs the correction to the position and the instantaneous energy consumption, while it adapts the control $\mathbf{u}_k$ in function of the TEE and QoS parameters.

A. Model

The state is the UAV's position in space and the energy evolution in time. Despite we show a linear relation between instantaneous energy and 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.

Starting with a position $\mathbf{p} \in \mathbb{R}^3$ in the 3D Euclidean space w.r.t. some inertial navigation frame $\mathcal{O}_W$, we build a guidance action–which allows the *position evolution* along the 3-axis–to the path to follow using a vector field [20]. We build the path with the TEE, being such function satisfied $\varphi(\mathbf{p}) \to 0$ for all the approaching points.

We build the *energy evolution* $\mathbf{q} \in \mathbb{R}^j$ using Fourier analysis (the meaning of j is clarified to the reader in Subsection II-C) and decompose such evolution in the energy due to the trajectory (depending on TEEs), and computations (on QoS)–an approach adapted from our earlier work on computational energy analysis [21], [22], and energy estimation of a fixed-wing UAV [23].

B. Trajectory

We consider a non-holonomic 2D model of the UAV flying at an assigned altitude $h \in \mathbb{R}_{>0}$ (the requirement is eased in Section III to a set of altitudes $\mathbf{h}$)

$$\begin{cases} \dot{\mathbf{p}}(t) &= s\Psi(\psi(t)) + \mathbf{d}(t) \\ \dot{\psi}(t) &= u(\mathbf{p}(t)) \end{cases}, \tag{2}$$

where $\mathbf{p} \in \mathbb{R}^2$, $s \in \mathbb{R}$ is the airspeed (assumed constant), $\psi \in (-\pi, \pi]$ the attitude yaw angle and $\Psi(\psi) = \begin{bmatrix} \cos\psi & \sin\psi \end{bmatrix}^T$, $\mathbf{d} \in \mathbb{R}^2$ is the wind vector (assumed $\|\mathbf{d}\| < s$, i.e., the constant airspeed is greater than the norm of the wind), and $u \in \mathbb{R}$ the guidance action–the angular velocity $\dot{\psi}$.

Let us define $\mathcal{P}_k$, the set that delimits all the possible deviations form the k-th TEE

$$\mathcal{P}_k := \{\mathbf{p} : \underline{c}_k \leq \varphi_k(\mathbf{p}, c_{k,1}, \dots, c_{k,\sigma}) \leq \overline{c}_k\}, \tag{3}$$

where $\underline{c}_k, \overline{c}_k$ are the bounds from the mission $\mathcal{M}$, that disclose the area where TEE $\varphi_k : \mathbb{R}^2 \times \mathbb{R}^\sigma \to \mathbb{R}$ is free to evolve using controls $\mathbf{c}_k := c_{k,1}, \dots, c_{k,\sigma}$.

The algorithm uses the concept to select $\varphi(\mathbf{p}, \mathbf{c}_k) = c_k \in \mathbb{R}$ with the highest energy value under the energy budget constraints.

For the purpose, we design a guidance action u that heads to such TEE by minimizing the norm $\|\varphi_k(\mathbf{p}) - c_k\|$. Let us define $\Phi := \varphi_k(\mathbf{p}) - c_k$. The direction to follow can be expressed as the desired velocity vector

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

where $\nabla\Phi \in \mathbb{R}^2$ is defined as the gradient of Φ at the point $\mathbf{p}$ (i.e., its vector field), 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 $\chi \in (-\pi, \pi]$ due to the atmospheric interference.

Let us further define $\hat{\mathbf{p}} := \mathbf{p}/\|\mathbf{p}\|$, the desired course heading rate $\dot{\chi}_d$ is computed by sensing the position $\mathbf{p}$, the ground velocity $\dot{\mathbf{p}}$, and is expressed

$$\begin{aligned} \dot{\chi}_d(\mathbf{p}) = -E\frac{\dot{\mathbf{p}}_d}{\|\dot{\mathbf{p}}_d\|^2} \cdot \\ \left(E\hat{\dot{\mathbf{p}}}_d\hat{\dot{\mathbf{p}}}_d^T E\left((E - k_e\Phi)H(\Phi)\dot{\mathbf{p}} - k_e\nabla\Phi^T\dot{\mathbf{p}}\nabla\Phi\right)\right)^T, \end{aligned} \tag{5}$$

where $H(\cdot)$ is defined as the Hessian operator and $\dot{\mathbf{p}}_d := \dot{\mathbf{p}}_d(\mathbf{p})$ for brevity; the physical meaning is that the curvature of the desired trajectory has to be known in order to be tracked.

The guidance action can be expressed

$$u(\mathbf{p}, \psi) = \frac{\|\dot{\mathbf{p}}\|}{s\cos\gamma}\left(\dot{\chi}_d + k_d\hat{\dot{\mathbf{p}}}^T E\hat{\dot{\mathbf{p}}}_d\right), \tag{6}$$

where $\gamma = \cos^{-1}\left(\hat{\dot{\mathbf{p}}}^T\Psi(\psi)\right)$ is the sideslip angle, $k_d \in \mathbb{R}_{\geq 0}$ adjusts the speed of convergence of $\dot{\mathbf{p}}_d$, and $\dot{\chi}_d := \dot{\chi}_d(\mathbf{p})$ is given in Equation (5).

C. Energy evolution due to trajectory

The energy evolution analysis necessitates the following realistic assumption.

Assumption 2.1: The trajectory is periodic, in the sense that it presents repetitive patterns.

Formally, given two time instants $k_1, k_2 \in \mathbb{T}$ s.t. $k_1 > k_2$ and a value $n \in \mathbb{R}_{\geq 0}$, there exist an arbitrary constant displacement $e \in \mathbb{R}$

$$\|\mathbf{p}_k - \mathbf{p}_{k+n}\| = e\ \ \forall k \in [k_1, k_2]. \tag{7}$$

We show in Section IV the assumption being eased in practice to a set $\mathbb{E} \subset \mathbb{R}$, or omitted under specific conditions.

Let us consider a Fourier series $f : \mathbb{R}_{\geq 0} \to \mathbb{R}$ of an arbitrary order $r \in \mathbb{Z}_{\geq 0}$ for the purpose of energy estimation of such a periodic trajectory

$$f(t) = \sum_{n=0}^{r} a_n \cos \frac{nt}{\xi} + b_n \sin \frac{nt}{\xi}, \tag{8}$$

where $\xi \in \mathbb{R}$ is the characteristic time, and $a_n, b_n \in \mathbb{R}$ for $n \in \{0, \dots, r\}$ the Fourier series coefficients.

Suppose no disturbances in form of $\mathbf{w}_k \in \mathbb{R}^j, v_k \in \mathbb{R}$ accounting otherwise for the unknown state and output. The non-linear model in Equation (8) can be expressed using an equivalent linear discrete time-invariant state-space model

$$\begin{cases} \mathbf{q}_{k+1} & = A\mathbf{q}_k + B\mathbf{u}_k + \mathbf{w}_k \\ y_k & = C\mathbf{q}_k + v_k \end{cases}, \tag{9}$$

where $y_k \in \mathbb{R}_{\geq 0}$ is the instantaneous energy consumption. We prove formally in the Theorem 3.1 the instantaneous energy being obtained as a linear combination of the state. The state $\mathbf{q}$ mimics the original Fourier series coefficients

$$\begin{aligned} \mathbf{q}_k &= \begin{bmatrix} \alpha_0 & \alpha_1 & \beta_1 & \cdots & \alpha_r & \beta_r \end{bmatrix}^T, \\ A &= \begin{bmatrix} 1 & & & \\ & A_1 & & \\ & & \ddots & \\ & & & A_r \end{bmatrix}, A_n = \begin{bmatrix} 0 & \frac{n}{\xi} \\ -\frac{n^2}{\xi^2} & 0 \end{bmatrix}, \\ C &= \begin{bmatrix} 1 & 1 & 0 & \cdots & 1 & 0 \end{bmatrix}, \end{aligned} \tag{10}$$

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 remaining.

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

$$\begin{aligned} \mathbf{u}_k &= \begin{bmatrix} g(\mathcal{C}_k) - g(\mathcal{C}_{k-1}) & \mathbf{c}_k - \mathbf{c}_{k-1} \end{bmatrix}^T \\ B &= \begin{bmatrix} 1 & \omega_{k,1} & \cdots & \omega_{k,\sigma} \\ & 0 & & \\ & & \ddots & \\ & & & 0 \end{bmatrix} \end{aligned} \tag{11}$$

where $\mathcal{C}_k$ is defined in Subsection II-D, $\mathbf{u}_k \in \mathbb{R}^l$ 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 TEE parameter to the instantaneous energy. Equation (11) accounts for the energy due to the computations. The energy due to the change of explicit trajectory equation parameters is merely a linear combination of the gain factor and the value of the TEE. Nevertheless, the change updates the trajectory 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 radius of a circular TEE will add a negative contribution, the simulate the lowering of instantaneous energy consumption.

In the case of the system behaving ideally (i.e., with zero disturbances), we expect a set of states evolving accordingly to their outputs. Such observation is summarized in the following Lemma.

Lemma 2.2: Suppose the system of Equation (9) evolves with no disturbances ($\mathbf{w} = \mathbf{0}, v = 0$) and Assumption 2.1 holds, then

$$\|\mathbf{q}_{k,0}\| \geq \|\mathbf{q}_{k,1}\| \iff y_{k,0} \geq y_{k,1}. \tag{12}$$

Proof:

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

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D. 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 hence 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 (QoS).

Suppose the system is composed of σ ROS nodes. Let us define a computational control action

$$\mathcal{C}_k := \left\{ u : u \in \mathrm{QoS}_{k,n} \;\; \forall n \in \{0, \dots, \sigma - 1\}, \forall k \in \mathbb{T} \right\}, \tag{13}$$

where $\mathrm{QoS}_{k,n} : \mathbb{Z}_{\geq 0} \to \mathbb{Z}_{\geq 0}$ returns the n-th QoS value at time instant k, and $\mathcal{C}_k \in \mathbb{Z}^{\sigma}_{\geq 0}$ the set of σ QoS values. 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

$$y^c_k := g\left(\mathrm{QoS}_{k,0}, \dots, \mathrm{QoS}_{k,\sigma-1}\right) = g\left(\mathcal{C}_k\right). \tag{14}$$

The QoS parameters $\mathcal{C}_k$ can be subject to different constraints at different states. Physically, this means that the UAV can perform the ROS nodes within different QoS ranges in time while flying

$$\begin{aligned} \underline{\mathrm{QoS}}_{k,n} \leq \mathrm{QoS}_{k,n} &\leq \overline{\mathrm{QoS}}_{k,n}, \\ &\forall n \in \{0, \cdots, \sigma - 1\}, \forall k \in \mathbb{T}, \end{aligned} \tag{15}$$

where the values $\underline{\mathrm{QoS}}_{k,n}, \overline{\mathrm{QoS}}_{k,n}$ are retrieved from the mission $\mathcal{M}$.

III. Algorithm

Let us proof formally an important finding from Section II-A extensively used in the algorithm.

Theorem 3.1: Consider a continuously differentiable function $\varphi_k : \mathbb{R}^2 \times \mathbb{R}^\sigma \to \mathbb{R}$ at a time instant $k \in \mathbb{T}$. Assume Assumption 2.1 holds, the robots is free to move in $\mathcal{P}$ defined in (3), and is following φ with the direction $\dot{\mathbf{p}}_d$ defined in 4. Likewise in Lemma 2.2, the model behaves ideally. Then, the instantaneous energy consumption is a linear combination of the state

$$y_k = C\mathbf{q}_k = \sum_{n=0}^{r} \alpha_n, \tag{16}$$

where $\alpha_n \in \mathbf{q}_k$ are the $r+1$ state's components at k with r being a preassigned arbitrary order from (8), and C is described in Equation (10).

Proof: *

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—from here on work in progress—

A. State estimation

As the environment uncertainty and measurement error evolve in a normal distribution, we use a Kalman filter [24], [25] for the purpose of state estimation.

The prediction is done using

$$\hat{\mathbf{q}}_{k+1}^{-} = A\hat{\mathbf{q}}_k + B\mathbf{u}_k, \tag{17a}$$
$$P_{k+1}^{-} = AP_kA^T + Q, \tag{17b}$$

where $\hat{\mathbf{q}}_k^{-}, \hat{\mathbf{q}}_k \in \mathbb{R}^j$ depicts the estimate of the state before and after measurement (or simply estimate), and $P_k, P_k^{-} \in \mathbb{R}^{j \times j}$ the error covariance matrix (i.e., the variance of the estimate).

The estimation of the state and the update of the predicted output is done using

$$K_k = (CP_{k+1}^{-}C^T + R)^{-1}(P_{k+1}^{-}C^T), \tag{18a}$$
$$\hat{\mathbf{q}}_{k+1} = \hat{\mathbf{q}}_{k+1}^{-} + K_k(y_k^s + y_k^c - C\hat{\mathbf{q}}_{k+1}^{-}), \tag{18b}$$
$$P_{k+1} = (I - K_kC)P_{k+1}^{-}, \tag{18c}$$
$$\hat{y}_k = C\hat{\mathbf{q}}_{k+1}, \tag{18d}$$

where $K_k \in \mathbb{R}^j$ is the gain of the Kalman filter, and I the identity matrix. y_k^s, y_k^c are the instantaneous energy readings: $y_k^s \in \mathbb{R}_{\geq 0}$ the robot sensor, i.e., the energy due to the trajectory, and y_k^c the energy of a given software configuration described in Equation (14). The noise covariance matrices $Q \in \mathbb{R}^{j \times j}, R \in \mathbb{R}$ indicates the uncertainty and measurement error covariance respectively, and $\hat{y}_k \in \mathbb{R}_{\geq 0}$ is the estimated energy.

Equations (17–18) converge to the predicted energy evolution as follows. An initial guess of the values $\hat{\mathbf{q}}_0, P_0$ is derived empirically from collected data. It is worth considering that an appropriate guess of these parameters allows the algorithm to converge to the desired energy evolution in a shorter amount of time. The tuning parameters Q, R are also derived from the collected data, and may differ due to i.e., different sensors used to measure the instantaneous energy consumption, or different atmospheric conditions accounting for the process noise.

At time $k = 0$, the initial estimate before measurement of the state and of the error covariance matrix is updated in Equation (17a) and (17b) respectively. The value of $\hat{\mathbf{q}}_1^{-}$ is then used in Equation (18b) to estimate the current state along with the data from the sensor y_0 (e.g., the energy sensor of the flight controller of the fixed-wing craft), where the sensor noise covariance matrix R accounts for the amount of uncertainty in the measurement. The estimated output $\hat{y}_0$ is then obtained from Equation (18d). The algorithm is iterative. At time $k = 1$ the values $\hat{\mathbf{q}}_1, P_1$ computed at previous step are used to estimate the values $\hat{\mathbf{q}}_2, P_2$, and y_1.

B. Optimal control action

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C. Deployment algorithm

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IV. Evaluation

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V. Conclusion and Future Work

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