Beyond Traditional Energy Planning: the Weight of Computations in Planetary Exploration

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***Abstract*— The paper proposes a mission-aware energy planning strategy that highlights the weight of computations on the overall energy budget of possible future autonomous space robots for planetary exploration programs. The planning strategy addresses the problem of the limited power of such robots by extending some technical breakthroughs in the energy planning for autonomous terrestrial robots and attempting to apply them to the planetary exploration context. It saves energy by changing the trajectory and computation specific parameters during the mission as the robot batteries drain, accounting for a possible mission extension. It focuses on aspects of a space mission, such as its periodicity and uncertainty.**

I. Introduction

The planetary rovers launched recently by the United States [1] and China [2] are scheduled to land onto the surface of the red planet in 2021, proving once more that no other planet among the eight in the Solar System has received as much attention as Mars. With these recent developments–which differ significantly by technology and scopes from the first space probes to fly by the planet in the 1960s–a renewed and growing interest is being seen in a wider context of planetary exploration programs.

The deployment and design of such programs introduce significant challenges and provide the scientific community use-cases of extreme environments with increasing demands for maneuverability, durability, weight, and power. The presented approach proposes a *mission-aware energy planning strategy* and highlights the role of *computational power demands* over traditional energy planning of forthcoming robots for planetary exploration programs. Parameters, such as the Quality of Service (QoS) of the onboard computations and the trajectory explicit equations (TEEs), characterize each mission phase and defines the means by which the power is varied. The approach deals with uncertainty by sensing the environment and adapting the parameters thorough the mission while optimizing the power demands.

The recent deployment to Mars of the National Aeronautics and Space Administration (NASA) rotorcraft Ingenuity–a small autonomous robot bolted in the undercarriage of the rover Perseverance [3]–is of particular incentive to the approach by means of presenting an energy-critical space mobile robot. The rotorcraft is powered entirely by six lithium-ion batteries and is first of its kind to feature a semi-autonomous flight on another planet [4]. The batteries will be charged solely by the rotorcraft's solar panel once the robot will be fully deployed on Mars–a difference compared to the Mars Perseverance rover powered by the natural decay of the radioisotope plutonium-238 [5]. The solar power source enables the investigation of mission-specific optimization strategies, by e.g., decreasing space robot computations during shadow mission phases and adapting the trajectory to maximize solar exposure.

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II. Energy Planning

It's of no surprise that different optimization strategies are not a new concept to the terrestrial robotic counterparts, including numerous contributions in the setting of energy planning. The approach extends some of these technical breakthroughs and attempts to apply them in a planetary exploration context. A conventional approach to address power demands for grounded mobile robots [6], focuses on optimizing the trajectory. Other studies [7] of coupling the energy due to the computations performed and the trajectory traveled, inspire the presented approach and extend into an automatic modeling tool in the author's previous work [8].

Terrestrial rotorcrafts have been obvious objects of recent research interest with approaches such as the generation of efficient trajectories [9].

A. Moving on another planet: energy due to trajectory

The approach addresses the motion using TEEs $\varphi : \mathbb{R}^2 \to \mathbb{R}$, a mathematical abstraction which represents the path to follow. Given a point $\mathbf{p} \in \mathbb{R}^2$ with respect to some inertial navigation frame $\mathcal{O}_M$, the set

$$\mathcal{P} := \{\mathbf{p} : \underline{c} \leq \varphi(\mathbf{p}) \leq \overline{c}\}, \tag{1}$$

discloses all the possible paths within the boundaries $\underline{c} \in \mathbb{R}_{\leq 0}, \overline{c} \in \mathbb{R}_{\geq 0}$. The boundaries $\underline{c}, \overline{c}$ are retrieved from the mission specification, a lookup table.

The concept is used to select $c : \underline{c} \leq c \leq \overline{c}$ with the highest energy value under the energy budget constraints from a set of ρ possible values. Physically, one can, e.g., use the equation of an ellipse as TEE. A variation in c impacts the length of the semi-major and -minor axis.

The direction to follow is derived using vector field [10]

$$\dot{\mathbf{p}}_d(\mathbf{p}) := \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \nabla\mathit{\Phi} - k_e \mathit{\Phi} \nabla\mathit{\Phi}, \tag{2}$$

where $\mathit{\Phi} := \varphi(\mathbf{p}) + c$, $\nabla\mathit{\Phi}$ is the vector field, the matrix specifies the direction, and $k_e \in \mathbb{R}_{\geq 0}$ speed of convergence.

One can easily observe a certain level of *periodicity* for planetary exploration programs, i.e., each mission presents repetitive patterns. Consequently, a Fourier series of order r suits the energy analysis as, by intuition, it will evolve also periodically. Another observation concerns the *uncertainty* which affects the energy evolution of space robots, being such evolution difficult to predict by terrestrial means. To address both, the approach proposes a harmonic oscillator in its state-space representation, and a state observer–a Kalman filter–for the purpose of estimating the energy state $\mathbf{q}$

$$\begin{cases} \mathbf{q}_{k+1} &= A\mathbf{q}_k + B\mathbf{u}_k + \mathbf{w}_k \\ y_k &= C\mathbf{q}_k + v_k \end{cases}, \tag{3}$$

where $\mathbf{w}_k \in \mathbb{R}^j$ accounts for the environment uncertainty, and $v_k \in \mathbb{R}$ for the measurement error, further

$$\begin{aligned} \mathbf{q}_k &= \begin{bmatrix} a_0 & a_1 & b_1 & \cdots & a_r & b_r \end{bmatrix}^T, \\ A &= \begin{bmatrix} 1 & & & \\ & A_1 & & \\ & & \ddots & \\ & & & A_r \end{bmatrix}, \ A_n = \begin{bmatrix} 0 & \frac{n}{\xi} \\ -\frac{n^2}{\xi^2} & 0 \end{bmatrix}, \\ C &= \begin{bmatrix} 1 & 1 & 0 & \cdots & 1 & 0 \end{bmatrix}, \end{aligned} \tag{4}$$

where $\mathbf{q} \in \mathbb{R}^j$ given $j := 2r + 1$ mimics the original coefficients of the series, $\xi \in \mathbb{R}$ is a characteristic time, $C \in \mathbb{R}^j$, $A \in \mathbb{R}^{j \times j}$, and each oscillator A_n represents a given order of the series. The unspecified elements of A are zeros.

B. Sensing on another planet: energy due to computations

The energy cost of performing a given mission specification, for instance, the ability to detect certain patterns on Mars using a convolutional neural network (CNN) in a hypothetical future mission, is evaluated using an empirical approach. The automatic modeling tool [8], measures the energy cost of a subset of possible computations and uses a multivariate linear regression for the remaining.

Such an energy cost is varied using QoS within given boundaries $\underline{\mathrm{QoS}}_n(k) \leq \mathrm{QoS}_n(k) \leq \overline{\mathrm{QoS}}_n(k)$ retrieved from the mission specification (along $\underline{c}, \overline{c}$). For instance, one can vary the frames-per-second rate of a given CNN algorithm. If the mission consists of a set $\mathbf{s}_k$ of σ QoS ranges, then

$$d(\mathbf{s}_k) = d\left(\mathrm{QoS}_0(k), \ldots, \mathrm{QoS}_{\sigma-1}(k)\right), \tag{5}$$

where $d : \mathbb{Z}^{\sigma}_{\geq 0} \to \mathbb{R}_{\geq 0}$ defines the energy cost difference obtained interrogating the modeling tool.

TEEs parameters and QoS ranges account for the changes in the energy due to trajectory and computations respectively, with the change being caused by variations in control $\mathbf{u}_k$ in Equation (3). Specifically, a possible implementation is

$$\mathbf{u}_k = \begin{bmatrix} d(\mathbf{s}_k) \\ c_0 \\ \vdots \\ c_{\rho-1} \end{bmatrix}, \ B = \begin{bmatrix} 1 & & & \\ & 0 & & \\ & & \ddots & \\ & & & 0 \end{bmatrix}, \tag{6}$$

where $\mathbf{u}_k \in \mathbb{R}^l$ is the control given $l := 1 + \rho$, and $B \in \mathbb{R}^{j \times l}$ is the input matrix. The first column in the first row of the matrix is 1, while all the other items are 0, which adds the energy due to the computations. The energy due to the trajectory is added indirectly, meaning that the readings from the sensors accounts for changes in the observed state $\mathbf{q}$.

III. The Weight of Computations

Past planetary vehicles, such as the Mars rovers, have had extremely limited computational resources as a result of large temperature changes and high radiation levels [11]. However, the recent introduction of a rotorcraft as a companion, and the increasing demand for autonomy, challenge the traditional computational model and perhaps justify the presented approach. Each mission to Mars uses more control software than all missions before it combined [12]. And controls consist of only one aspect of modern planetary exploration programs. The future space robots are expected to automatically learn properties of the terrain and use such knowledge to predict future actions [11].

Preliminary data indicates a potential mission extension of a space robot: a tiny planetary exploration rover [13] consumes on average 22 watts, and a modern embedded device (such as NVIDIA Jetson Nano) 10 watts while performing CNN at a high frames-per-second rate, a considerable amount of energy in a scenario where the two coexist together. Such a calculation, however, requires further investigation–the two systems have been analyzed separately.

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