Mars:

Multi-Agent Reinforcement learning System for coordinating spacecraft swarms in Martian orbit

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Abstract

Orbiting spacecraft swarms for mars exploration face challenges due to communication delays from Earth and a lack of global positioning system (GPS). Due to the complexity of the dynamical environment, traditional methods lack the required robustness. Current methods like the spherical harmonic representation are effective outside of a specific radius but diverges within the Brillouin sphere and in the presence of multi-body systems. We propose a combined computational method that utilizes physics-informed neural networks (PINNs) with reinforcement learning models to create autonomous satellite controls for these orbiting swarms.

These PINNs will model Mars-centric orbital dynamics including perturbations from Phobos and Deimos, atmospheric drag, and planetary oblateness. The multi-agent reinforcement learning model will be utilized for formation keeping, collision avoidance, and required reconfiguration. They will be trained on current Martian orbiter data, and multi-agent reward functions for fuel conservation and safety and maintain orbital integrity. The model will support 5-50 spacecraft with varied onboard missions and orbits.

Introduction

Physics-Informed Neural Networks (PINNs) optimize weights and biases between hidden layers to create a model that can predict high-order functions in a robust, and efficient manner, whilst holding the solution to physical laws. These are perfectly suited for orbital solutions due to their difficult solutions.

Background

Martin & Schaub 2022 showed that PINNs were better at modeling gravitational potential fields around more spherical bodies. PINNs were used to predict and model the gravitational field around the Earth and Moon (fig 1). While both worked better than traditional methods, the model worked significantly better for the Earth because of the "smoothness factor" (S_p) of the planet. Which takes the tallest point on the planet (p_T) and the lowest point on the planet (p_L), and planetary radius,

$$S_p = \frac{p_T - p_L}{r_p}$$

Earth: $s = 0.00311$
Moon: $s = 0.01145$
Mars: $s = 0.00853$

The smoothness factor of Mars is closer to Earth's so the PINN should be significantly better at modeling the gravitational field around Mars than current computational methods.

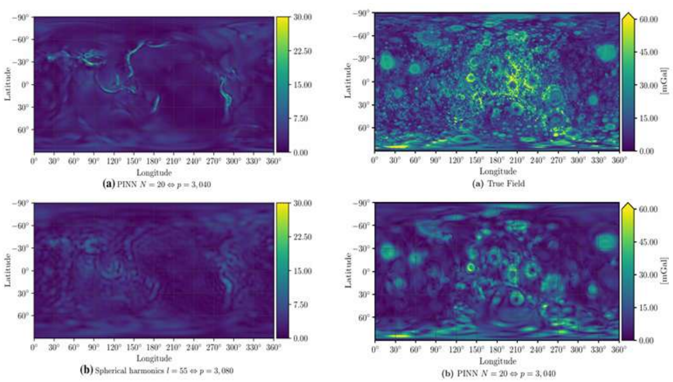

Fig 1. Gravitational potential of the Earth, modeled with a PINN (top left), gravitational potential of Earth, modeled using spherical harmonics (bottom left). Gravitational potential of Moon, modeled using spherical harmonics (top right). Gravitational potential of Moon, modeled using spherical harmonics (bottom right). Martin &Schaub 2022

Methods

The following equations model the controls equations for an n-body problem with no maneuvers. These equations form the basis for the orbital physics ODE, including orbital perturbations from J_2 and atmospheric drag on the satellite.

$$\boldsymbol{R}_1 = \begin{Bmatrix} X_1 \\ Y_1 \\ Z_1 \end{Bmatrix}, \quad \boldsymbol{R}_2 = \begin{Bmatrix} X_2 \\ Y_2 \\ Z_2 \end{Bmatrix}, \quad \cdots \quad \boldsymbol{R}_n = \begin{Bmatrix} X_n \\ Y_n \\ Z_n \end{Bmatrix}$$

$$\boldsymbol{v}_1 = \begin{Bmatrix} \dot{X}_1 \\ \dot{Y}_1 \\ \dot{Z}_1 \end{Bmatrix}, \quad \boldsymbol{v}_2 = \begin{Bmatrix} \dot{X}_2 \\ \dot{Y}_2 \\ \dot{Z}_2 \end{Bmatrix}, \quad \cdots \quad \boldsymbol{v}_3 = \begin{Bmatrix} \dot{X}_n \\ \dot{Y}_n \\ \dot{Z}_n \end{Bmatrix}$$

$$\boldsymbol{a}_1 = \begin{Bmatrix} \ddot{X}_1 \\ \ddot{Y}_1 \\ \ddot{Z}_1 \end{Bmatrix} = \begin{Bmatrix} \sum_{i=1}^{n} \frac{Gm_i(X_i - X_1)}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(X_i - X_1)}{R_{1,i}}\left(5\frac{(Z_i - Z_1)^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \\ \sum_{i=1}^{n} \frac{Gm_i(Y_i - Y_1)}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(Y_i - Y_1)}{R_{1,i}}\left(5\frac{(Z_i - Z_1)^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \\ \sum_{i=1}^{n} \frac{Gm_i(Z_i - Z_1)}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(Z_i - Z_1)}{R_{1,i}}\left(5\frac{(Z_i - Z_1)^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \end{Bmatrix}, where\ i \neq 1$$

$$\boldsymbol{a}_2 = \begin{Bmatrix} \ddot{X}_2 \\ \ddot{Y}_2 \\ \ddot{Z}_2 \end{Bmatrix} = \begin{Bmatrix} \sum_{i=1}^{n} \frac{Gm_i(X_i - X_2)}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(X_i - X_2)}{R_{1,i}}\left(5\frac{(Z_i - Z_2)^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \\ \sum_{i=1}^{n} \frac{Gm_i(Y_i - Y_2)}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(Y_i - Y_2)}{R_{1,i}}\left(5\frac{(Z_i - Z_2)^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \\ \sum_{i=1}^{n} \frac{Gm_i(Z_i - Z_2)}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(Z_i - Z_2)}{R_{1,i}}\left(5\frac{(Z_i - Z_2)^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \end{Bmatrix}, where\ i \neq 2$$

$$\vdots$$

$$\boldsymbol{a}_n = \begin{Bmatrix} \ddot{X}_n \\ \ddot{Y}_n \\ \ddot{Z}_n \end{Bmatrix} = \begin{Bmatrix} \sum_{i=1}^{n-1} \frac{Gm_i(X_i - X_{n-1})}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(X_i - X_1)}{R_{1,i}}\left(5\frac{(Z_i - Z_{n-1})^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \\ \sum_{i=1}^{n-1} \frac{Gm_i(Y_i - Y_{n-1})}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(Y_i - Y_{n-1})}{R_{1,i}}\left(5\frac{(Z_i - Z_{n-1})^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \\ \sum_{i=1}^{n-1} \frac{Gm_i(Z_i - Z_{n-1})}{R_{1,i}^3} - \frac{3}{2}\frac{J_2 G m_i r_p^2}{R_{1,i}^4}\frac{(Z_i - Z_{n-1})}{R_{1,i}}\left(5\frac{(Z_i - Z_{n-1})^2}{R_{1,i}^2} - 1\right) - \frac{\rho\, v_{rel}^2 A\, C_D}{2\, m_i} \end{Bmatrix}, where\ i \neq n$$

$$y = \lfloor \boldsymbol{R}_1\ \boldsymbol{R}_2\ \boldsymbol{R}_3\ \cdots\ \boldsymbol{R}_n\ \boldsymbol{v}_1\ \boldsymbol{v}_2\ \boldsymbol{v}_3\ \cdots\ \boldsymbol{v}_n \rfloor^T$$
$$\dot{y} = \boldsymbol{f}(t, \boldsymbol{y}) = \lfloor \boldsymbol{v}_1\ \boldsymbol{v}_2\ \boldsymbol{v}_3\ \cdots\ \boldsymbol{v}_n\ \boldsymbol{a}_1\ \boldsymbol{a}_2\ \boldsymbol{a}_3\ \cdots\ \boldsymbol{a}_n \rfloor^T$$

These equations can then be placed into our PINN (fig 2) to form the second loss function.

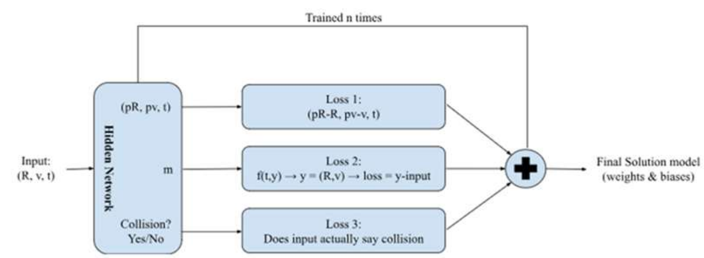

Fig 2. Basic outline for setup of physics-informed neural network to model the gravitational dynamics of an n-body system, integrate these models out and predict possible collisions.