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ROBUST PREDICTIVE ATTITUDE CONTROL WITH STOCHASTIC DYNAMICS

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Abstract. The aim of this work is to design a robust predictive attitude controller when the disturbance is not known and it is modelled based on the stochastic theory and not directly from the environment and its laws. The paper starts with a brief introduction about the interest of attitude control, the state of the art, the limitations and the objectives of the research work. Then it moves on the control model chosen for the work. The main part is related to the modelling of the stochastic disturbance and the actuation of the controller. The results obtained match the initial idea about the capability of the controller to work under an unknown disturbance torque. Indeed, the graphical results show, for all the different conditions considered, that the required attitude is always reached, meaning that the aim of this work was achieved.

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1. Introduction

Attitude control has been a crucial topic that engineers have focused on since the very first days of space exploration. Ensuring that a spacecraft is pointing the right direction is very important for many reasons, which might also differ based on the mission.

Model-based predictive control has been used and studied for many years. Its power is associated with the prediction of the future behaviour of the controlled system determining implicitly the control law to be applied. The foundation of MPC dates back to the late 70s and its potential was not only associated with the prediction but also to its capability to deal with non-linear models. With the development of new technologies, the computational time to solve a problem, which at the beginning was really high, began to decrease while the applicability of the MPC increased [1].

The outcomes of the studies over MPC, such as [2–4] underline the reliability and power of the Model-based Predictive Control in a lot of various environments.

The most difficult problem for the attitude control is linked to the disturbances that are associated with space missions, such as the gravity gradient, the solar radiation pressure, the magnetic field, the air drag, etc. These behave differently based on the different orbits that are considered and the dimensions of the spacecraft; thus wider modelling of these perturbations might not be straightforward as well as deal with all of them interacting together.

The purposes of this work are first of all to find an appropriate stochastic model of the attitude dynamics accounting for disturbance torque effects, then to propose a predictive disturbance torque estimation method, propose a robust predictive attitude control method based on predictive disturbance torque estimation and perform computational validation of the proposed control method using various realistic scenarios with actual spacecraft data.

The report will start introducing the control model used for the work, the theory of the attitude dynamics of a spacecraft and the application of the model to our case. Then the stochastic model for the environment will be introduced to test the control and observe how it will react and the results obtained.

2. Control model

2.1. State model

The content of this section is a brief summary about nonlinear predictive control [5–7].

The method taken into consideration for this discussion considers the system in the form

$$\begin{cases} \dot{\boldsymbol{x}}_1 = \boldsymbol{f}_1(\boldsymbol{x}) \\ \dot{\boldsymbol{x}}_2 = \boldsymbol{f}_2(\boldsymbol{x}) + \boldsymbol{B}_2(\boldsymbol{x})\boldsymbol{u} \end{cases} \tag{1}$$

By considering the vector $\boldsymbol{x} = [\boldsymbol{x}_1, \boldsymbol{x}_2]^T$, $\boldsymbol{f} = \begin{pmatrix} \boldsymbol{f}_1 \\ \boldsymbol{f}_2 \end{pmatrix}$, $\boldsymbol{G} = \begin{pmatrix} 0 \\ \boldsymbol{B}_2 \end{pmatrix}$ the system can be rewritten as

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}) + \boldsymbol{G}(\boldsymbol{x})\boldsymbol{u} \tag{2}$$

Note that the application of this model to our case is going to be presented in the next section. At this point what we want to do is to control the state $\boldsymbol{x}$ using the predictive control, considering that $\boldsymbol{f}_1$, $\boldsymbol{f}_2$ and $\boldsymbol{B}$ are non-linear. Considering Eq. (1), it is possible to define r_i (with $i = 1, 2$) as the relative degree of freedom of the state vector. In other words r_i, that is a scalar value, is the minimum number of times that

I need to differentiate x_i in order to obtain explicitly in its expression the dependence from the control $\boldsymbol{u}$.

At this point, to retrieve the expression of the state at time $t+h$, the Taylor expansion is introduced using the Lie derivative, in particular it is considered $\boldsymbol{v}(\boldsymbol{x}(t),h) = = (v_1,...,v_n)^T$ where

$$v_i = hL_f^0(f_i) + \frac{h^2}{2}L_f^1(f_i) + ... + \frac{h_i^r}{r_i}L_f^{r_i-1}(f_i), \quad i = 1,...,n \tag{3}$$

where the time-step $h > 0$ is a real number and f_i is the i-th component of $\boldsymbol{f}$ and the Lie derivative is expressed as

$$L_f^0(f_i) = f_i$$

$$L_f^1(f_i) = \frac{\partial f_i}{\partial \boldsymbol{x}}\boldsymbol{f} \tag{4}$$

$$L_f^2(f_i) = \frac{\partial L_f^1(f_i)}{\partial \boldsymbol{x}}\boldsymbol{f}$$

so that the approximation of x at $t+h$ is

$$\boldsymbol{x}(t+h) \approx \boldsymbol{x}(t) + \boldsymbol{v}(\boldsymbol{x}(t),h) + \Lambda(h)\boldsymbol{W}[\boldsymbol{x}]\boldsymbol{u}(t) \tag{5}$$

with $\Lambda \in R^{n\times n}$ being a diagonal matrix with elements defined as

$$\lambda_{ii}(h) = \frac{h^{r_i}}{r_i}, \quad i = 1,...,n \tag{6}$$

and $\boldsymbol{W} \in R^{n\times m}$ is a matrix whose generic row i is such that

$$w_i = \{L_{g_1}[L_f^{r_i-1}(x_i)],...,L_{g_m}[L_f^{r_i-1}(x_i)]\}, \quad i = 1,...,n \tag{7}$$

where the functions $g_1,...,g_m$ are the columns of matrix $\boldsymbol{G}$ and the Lie derivative with respect to g_j is defined in a similar way as in Eq. (4). Once the tracking error is defined as $\boldsymbol{e}(t) = \boldsymbol{x}(t) - \boldsymbol{q}(t)$, and once the reference function $\boldsymbol{q}(t)$ is approximated using a Taylor expansion up to r_i-th order

$$\boldsymbol{q}(t+h) \approx \boldsymbol{q}(t) + \boldsymbol{d}(t,h) \tag{8}$$

$$d_i(t,h) = h\dot{q}_i(t) + \frac{h^2}{2}\ddot{q}_i(t) + ... + \frac{h_i^r}{r_i}q_i^{(r_i)}(t), \quad i = 1,...,n \tag{9}$$

the performance index is presented as

$$J[\boldsymbol{u}(t)] = \frac{1}{2}[\boldsymbol{e}(t+h)]^T\boldsymbol{Q}[\boldsymbol{e}(t+h)] + \frac{1}{2}\boldsymbol{u}^T(t)\boldsymbol{R}\boldsymbol{u}(t) \tag{10}$$

Minimizing this expression with respect to $\boldsymbol{u}(t)$ yields to the controller

$$\boldsymbol{u}(t) = -\{[\boldsymbol{\Lambda}(h)\boldsymbol{W}(\boldsymbol{x})]^T\boldsymbol{Q}\boldsymbol{\Lambda}(h)\boldsymbol{W}(\boldsymbol{x})+\boldsymbol{R}\}^{-1}\times\{[\boldsymbol{\Lambda}(h)\boldsymbol{W}(\boldsymbol{x})]^T\boldsymbol{Q}[\boldsymbol{e}(t)+\boldsymbol{v}(\boldsymbol{x},t)-\boldsymbol{d}(t,h)]\} \tag{11}$$

2.2. Attitude dynamics

To describe the attitude motion of our spacecraft, we will use the Euler equations where we will consider the angular rates and the quaternions as follows:

$$\begin{cases} \dot{\omega}_1 = b_1\omega_3\omega_2 \\ \dot{\omega}_2 = b_2\omega_1\omega_3 \\ \dot{\omega}_3 = b_3\omega_2\omega_1 \end{cases} \tag{12}$$

$$\dot{\boldsymbol{q}} = \frac{1}{2}\begin{bmatrix} 0 & -\omega_1 & -\omega_2 & -\omega_3 \\ \omega_1 & 0 & \omega_3 & -\omega_2 \\ \omega_2 & -\omega_3 & 0 & \omega_1 \\ \omega_3 & \omega_2 & -\omega_1 & 0 \end{bmatrix}\boldsymbol{q} \tag{13}$$

2.3. Model Predictive Control law

Taking into consideration the system in Equation (1), we can define $\boldsymbol{x}_1 = \boldsymbol{q}$ and $\boldsymbol{x}_2 = \boldsymbol{\omega}$, then we can add the control to Equation (12) such that

$$\begin{cases} \dot{\omega}_1 = b_1\omega_2\omega_3 + u_1 \\ \dot{\omega}_2 = b_2\omega_1\omega_3 + u_2 \\ \dot{\omega}_3 = b_3\omega_2\omega_1 + u_3 \end{cases} \tag{14}$$

And we obtain our state system as

$$\begin{cases} \dot{\boldsymbol{q}} = \boldsymbol{M}(\boldsymbol{x})\boldsymbol{q} \\ \dot{\boldsymbol{\omega}} = \boldsymbol{f}(\boldsymbol{x}) + \boldsymbol{I}_3\boldsymbol{u} \end{cases} \tag{15}$$

where $\boldsymbol{I}_3$ is the identity matrix.

2.3.1. Defining matrices $\boldsymbol{W}$, $\boldsymbol{\Lambda}$ and vector $\boldsymbol{v}$

In our case, since the maximum order of the Taylor expansion is 2, the matrix $\boldsymbol{W}$ coming from Equation (11) can be built evaluating the double derivative of both $\boldsymbol{\omega}$ and $\boldsymbol{q}$ and use it in the expansion. Combining the results for quaternions and for the angular velocities and considering that this control law does not include the disturbance torque because it is assumed not to be known, we can write the value of $\boldsymbol{W}$, $\boldsymbol{\Lambda}$ and $\boldsymbol{v}$:

$$\boldsymbol{W} = \frac{1}{2}\begin{bmatrix} -q_2 & -q_3 & -q_4 \\ q_1 & -q_4 & q_3 \\ q_4 & q_1 & -q_2 \\ -q_3 & q_2 & q_1 \\ 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix} \tag{16}$$

$$\boldsymbol{\Lambda} = \frac{h}{2}\begin{bmatrix} h & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & h & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & h & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & h & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 \end{bmatrix} \tag{17}$$

$$\boldsymbol{v} = \begin{Bmatrix} \boldsymbol{v}_1 \\ \boldsymbol{v}_2 \end{Bmatrix} \tag{18}$$

where

$$\boldsymbol{v}_1 = h\dot{\boldsymbol{q}} + \frac{h^2}{2}\boldsymbol{C}(\boldsymbol{\omega})\boldsymbol{q} \tag{19}$$

$$\boldsymbol{v}_2 = h\begin{Bmatrix} b_1\omega_2\omega_3 \\ b_2\omega_1\omega_3 \\ b_3\omega_1\omega_2 \end{Bmatrix} \tag{20}$$

3. Control with stochastic disturbances

The aim of this work is to study the behaviour of the controller introduced in Section 2 when it is subjected to stochastic disturbances [7].

The system that we are now considering is the following:

$$\begin{cases} \dot{\boldsymbol{q}} = \boldsymbol{M}(\boldsymbol{x})\boldsymbol{q} \\ \dot{\boldsymbol{\omega}} = \boldsymbol{f}(\boldsymbol{x}) + \boldsymbol{I}_3\boldsymbol{u} + \boldsymbol{D}_\omega\boldsymbol{w}_\omega \end{cases} \tag{21}$$

that can be condensed in:

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}) + \boldsymbol{B}\boldsymbol{u} + \boldsymbol{D}\boldsymbol{w} \tag{22}$$

The main difference between the deterministic and the stochastic model is that in this second case we also have the dependence on the variable $\boldsymbol{w}$, which is a random vector such that its first derivative has a normal distribution. Therefore, it is built as the density function knowing the mean value and the covariance matrix. In our model

$$\boldsymbol{w} \in \mathbb{R}^3 \quad and \quad \boldsymbol{D} \in \mathbb{R}^{7\times 3}$$

As we can see from Equation (21), the disturb $\boldsymbol{w}$ acts only on the angular velocity, this happens because $\boldsymbol{q}$ is a fictitious operator that has no physical meaning, so it is impossible that a real perturbation directly modify it. Consequently, the matrices $\boldsymbol{D}$ and $\boldsymbol{B}$ are defined as follows

$$\boldsymbol{D} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad \boldsymbol{B} = \begin{bmatrix} \mathbf{0}^{4\times 3} \\ \boldsymbol{I}_3 \end{bmatrix}$$

The estimation of the covariance matrix $\boldsymbol{W}$ comes from the availability of a set of measurements $\xi_1, \xi_2, ..., \xi_n$ at times $t_1, t_2, ..., t_n$, from which

$$\boldsymbol{W} = E[(\xi - \overline{\xi})(\xi - \overline{\xi})^T] \tag{23}$$

where E is the expected value and $\overline{\xi}$ is the mean of the measurements. This can be solved using the Monte Carlo approximation such that:

$$\boldsymbol{W} = \frac{1}{N-1}\sum_{k=1}^{N}(\xi_k - \overline{\xi})(\xi_k - \overline{\xi})^T \tag{24}$$

3.1. Stochastic model

Dealing with stochastic processes requires the solution of Stochastic Differential Equations (SDEs) to retrieve the new equation of motion.

A stochastic process can be seen as a process where what happens at time t_k is completely disconnected and unrelated from what happens at time t_{k-1} and at time t_{k+1}.

In our case, in order to create the model of the stochastic disturbance, it was necessary to provide a covariance matrix and a mean value so that the probability density function related to them would be evaluated. The covariance matrix was built based on some measurements coming from the environment, as well for the mean value. In a real case those measurements would come from real data that a spacecraft has detected in its orbit. In our discussion the data are coming from a random sampling of a deterministic torque defined as:

$$\boldsymbol{m}_e = \begin{Bmatrix} a_1 \sin\left(\frac{4\pi}{T}t\right) \\ a_2 \sin\left(\frac{4\pi}{T}t\right) \\ a_3 \sin\left(\frac{4\pi}{T}t\right) \end{Bmatrix} \tag{25}$$

where a_i are the amplitudes, T is the period and t is the simulation time.

The choice of a sinusoidal function as a disturb is related to the fact that it is a simplified representation of the real disturbances that are acting on the spacecraft such as the Gravity Gradient, the Solar Radiation Pressure and the Magnetic Field. Indeed, as a first analysis, the magnitude of the amplitudes a_1, a_2 and a_3 is the same as the magnitude of the Gravity Gradient in a LEO orbit that is 10^{-5}.

Concretely the values selected for the amplitudes a_i in Equation (25) are:

a_1	$-6 \cdot 10^{-5}$
a_2	$1 \cdot 10^{-5}$
a_3	$8 \cdot 10^{-5}$

Instead, the period chosen is T = 100 s.

At each time step, 200 out of 10000 values of the torque were sampled in a completely random manner, then the mean value and the covariance matrix were evaluated using the command `mean` and `cov` on Matlab®. Later the normal density function was determined in order to obtain the values of the stochastic torque $\boldsymbol{w}$ with the command `mvnpdf`, and it was differentiated according to the theory of the SDEs where we considered the stochastic derivative as $\boldsymbol{D}(w_k - w_{k-1})$.

In the meantime the ODE associated with spacecraft was solved independently. At the end, the two parts of the derivative were summed together in order to obtain the state of the system.

4. Data

For the simulation, the controller is supposed to be mounted on a Rapid Eye – Micro-spacecraft, whose moments of inertia are considered to be:

I_1	19.5 kgm^2
I_2	19 kgm^2
I_3	12.6 kgm^2

For the validation of the control, three different cases were taken in to consideration, each one with its own initial and desired attitude[1].

	$\boldsymbol{\omega}_0$	$\boldsymbol{\theta}_0$	$\boldsymbol{\omega}_{des}$	$\boldsymbol{\theta}_{des}$
Case 1	[0;0;0]	[0.1;0.2;0]	[0;0;0]	[0;0;0]
Case 2	[0;0;0]	[0.1;0.2;0]	[0;0;0]	$\left[\frac{\pi}{10};\frac{\pi}{6};\frac{\pi}{3}\right]$
Case 3	[0;0;0]	[0.1;0.2;0]	[0;0;0]	$\left[\frac{\pi}{10};-\frac{\pi}{6};\frac{\pi}{3}\right]$

As it is possible to see, for all the three cases considered, both initial and desired attitude have zero angular rates, this is because the controller at first it is evaluated just in a rest-to-rest slew manoeuvre.

For all of the three cases, the time step h considered is:

h	0.01 s

and the simulation time:

t_0	0 s
t_f	10000 s

5. Optimal choice of the matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$

To build a robust controller, it is necessary to perform an optimal choice of the matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$.

5.1. Matrix $\boldsymbol{Q}$

The most important part is the matrix $\boldsymbol{Q}$ because it is the one associated with the error to be minimized in Equation (10), which means that its optimal choice leads the control to act faster and better on the spacecraft.

5.1.1. Restricted LQR

To find the matrix $\boldsymbol{Q}$, the restricted LQR problem is used. Indeed, if the normal LQR works in the whole domain, but since in our case the system is not controllable in all state space, such as for angles more than 3π or less than -3π that are not reached by the spacecraft, the restricted one finds the matrix $\boldsymbol{P}$ just around the operating domain. The matrix $\boldsymbol{Q}$ is later built as follows

$$\boldsymbol{Q} = \lambda_{max}\boldsymbol{I}^{7\times 7} \tag{26}$$

[1] Note that the attitude is expressed using Euler angles, but in the code these are converted in quaternions for all the calculations.

where λ_{max} is the maximum eigenvalue of the matrix $\boldsymbol{P}$ and $\boldsymbol{I}^{7\times7}$ is a 7×7 identity matrix.

For our case the value of the maximum eigenvalue of $\boldsymbol{P}$ is

$$\lambda_{max} = 4.46\times10^{15} \tag{27}$$

5.1.2. Robustness

The robustness of the solution of λ_{max} comes from the fact that the LQR problem was solved considering a system that requires more energy to be controlled than the real one, meaning that if the controller is capable of controlling the worse system, it is certainly able to deal with the better one. This can be obtained by shifting the matrix $\boldsymbol{A}$ associated with our system of a value α, so that

$$\boldsymbol{A}_{worse} = \boldsymbol{A} + \alpha\boldsymbol{I}$$

5.2. Matrix R

The matrix R does not affect the controller in the convergence, as it only affects the magnitude of the control torque. This is because, as we can see in Equation (10), it acts directly on the control $\boldsymbol{u}$, meaning that its choice cannot influence the error $\boldsymbol{e}$. Indeed the matrix $\boldsymbol{R}$ can be chosen freely.

The fact that $\boldsymbol{R}$ acts on the control means that the greater its diagonal elements are the slower the stabilization will be and viceversa. This characteristic is really useful because it allows the designer to better match the mission requirements. Indeed, if we imagine a spacecraft with humans onboard the stabilization should not be fast, otherwise the crew will be affected by strong accelerations on their body. Moreover, the structural limits might also be considered, for instance a large satellite with a big mass might be not capable of performing a fast de-tumbling.

6. Results

6.1. Case 1

In this section the results for the simulation of Case 1 (Fig. 1) are presented, where both the initial and desired values for angular velocities are zero. For the angles, the initial condition $\boldsymbol{\theta}_0 = [0.1; 0.2; 0]$ and attitude to reach is $\boldsymbol{\theta}_{des} = [0; 0; 0]$.

6.2. Case 2

In this section the results for the simulation of Case 2 (Fig. 2) are presented, where both the initial and desired values for angular velocities are zero. For the angles, the initial condition is $\boldsymbol{\theta}_0 = [0.1; 0.2; 0]$ and attitude to reach is $\boldsymbol{\theta}_{des} = \left[\frac{\pi}{10}; \frac{\pi}{6}; \frac{\pi}{3}\right]$.

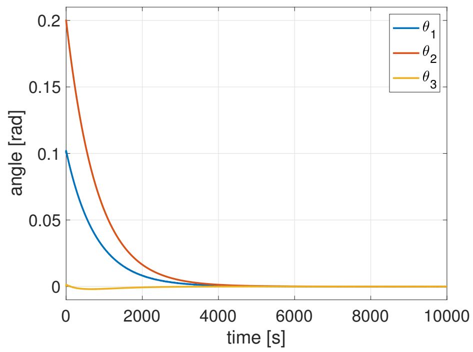

Fig. 1. Euler angles

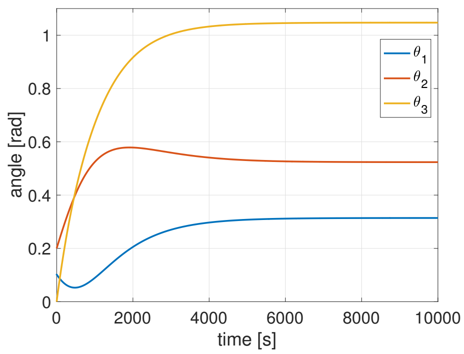

Fig. 2. Euler angles

6.3. Case 3

In this section the results for the simulation of Case 3 (Fig. 3) are presented, where both the initial and desired values for angular velocities are zero. For the angles, the initial condition is $\boldsymbol{\theta}_0 = [0.1; 0.2; 0]$ and attitude to reach is $\boldsymbol{\theta}_{des} = \left[\frac{\pi}{10}; -\frac{\pi}{6}; \frac{\pi}{3}\right]$.

6.3.1. Comments

In all the three conditions, the convergence of the attitude with the desired Euler angles is reached rapidly and smoothly, without any oscillations, bouncing or strong changes. This happens because the restricted LQR problem provides a matrix that increases the robustness of the control.

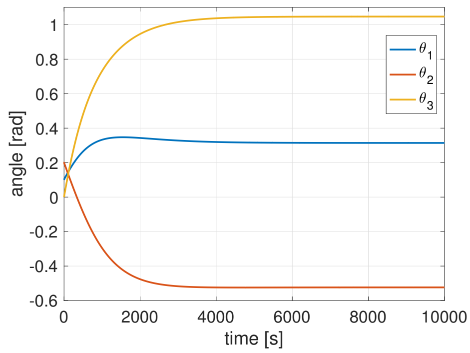

Fig. 3. Euler angles

7. Conclusions and future work

From the results obtained, it is possible to say that the controller is successful in stabilizing the spacecraft in the condition tested, under an unknown stochastic torque.

Indeed, the results presented before are the same obtained in the preliminary step of the evaluation of the controller under a deterministic torque, defined with the same sinusoidal function used to sample and build the stochastic model. This result has been very important for our discussion because it meant that the stochastic model used for the external torque was well-designed and well-representative of the "sampled" one.

The use of a sinusoidal function implies that its behaviour is highly dependent on the choice of amplitudes and period. For this reason, the controller was also tested with different values of these quantities and was found to be unaffected by these variations, always guaranteeing the stabilization even under strong and unrealistic conditions[2].

Knowing that it is virtually almost impossible to perfectly model the real environment where a spacecraft will operate, considering the disturbance torque as unknown and consequently representing it using the stochastic theory was proven to lead to good performances of the controller.

In the end it was confirmed that the controller performs better and stronger when the environment is modelled as stochastic and the matrix $\boldsymbol{Q}$ is the optimal one. Moreover, the future of this work might be associated with the testing using real measurements of the disturbances coming from an in-orbit spacecraft for the validation of the stochastic model, or with the studying of its behaviour when it is working with attitude determination sensors and actuators. Furthermore, the method can be also extended to deal with the current issues of controlling attitude, such as the use of magnetic torquers in LEOs that would allow to save a great amount of fuel, exploiting the external torques, such as the ones coming from the GG and the magnetic field.

[2] The results are not presented in this paper because not directly related to the topic.

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References

[1] Schwenzer, M., Ay, M., Bergs, T., & Abel, D. (2021). Review on model predictive control: An engineering perspective. *The International Journal of Advanced Manufacturing Technology*, *117*(5-6), 1327-1349. https://doi.org/10.1007/s00170-021-07682-3.

[2] Wang, P., Tang, G.J., Liu, L. H., & Wu, J. (2013). Nonlinear hierarchy-structured predictive control design for a generic hypersonic vehicle. *Science China Technological Sciences*, *56*(8), 2025-2036. https://doi.org/10.1007/s11431-013-5273-7.

[3] Guiggiani, A., Kolmanovsky, I., Patrinos, P., & Bemporad, A. (2015). Constrained model predictive control of spacecraft attitude with reaction wheels desaturation. *2015 European Control Conference (ECC)*. https://doi.org/10.1109/ecc.2015.7330731.

[4] Hegrenæs, Ø., Gravdahl, J.T., & Tøndel, P. (2005). Spacecraft Attitude Control using explicit model predictive control. *Automatica*, *41*(12), 2107-2114. https://doi.org/10.1016/j.automatica.2005.06.015.

[5] Lu, P. (1994). Nonlinear predictive controllers for continuous systems. *Journal of Guidance, Control, and Dynamics*, *17*(3), 553-560. https://doi.org/10.2514/3.21233.

[6] Carloni, G., & Bousson, K. (2016). A nonlinear control method for Autonomous Navigation Guidance. *International Review of Civil Engineering (IRECE)*, *7*(4), 102. https://doi.org/10.15866/irece.v7i4.10757.

[7] Crassidis, J.L., Markley, F.L., Anthony, T.C., & Andrews, S.F. (1997). Nonlinear predictive control of spacecraft. *Journal of Guidance, Control, and Dynamics*, 20(6), 1096-1103. https://doi.org/10.2514/2.4191.

[8] Panik, M.J. (2017). *Stochastic Differential Equations: An Introduction with Applications in Population Dynamics Modeling*. Wiley Blackwell.