

# INTELLIGENT CONTROL OF SPACECRAFT ATTITUDE USING REINFORCEMENT LEARNING

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The aim of this paper is to develop an effective algorithm for intelligent control of spacecraft based on reinforcement learning (RL) methods.

In the development and analysis of the algorithm, methods of theoretical mechanics, automatic control and stability theories, machine learning, and computer simulation were used. To increase the RL efficiency, a statistical model of spacecraft dynamics based on the concept of Gaussian processes was used. On the one hand, such a model allows one to use a priori information about the plant and is sufficiently flexible, and on the other hand, it characterizes uncertainty in the dynamics in the form of confidence intervals and can be refined during the spacecraft operation. In this case, the problem of control/state space analysis reduces to obtaining such measurements that narrow the confidence intervals. The familiar quadratic criterion, which allows one to take into account both the accuracy requirements and the control cost, was used as the reinforcement signal. An RL-based search for control actions was made using a control law iterative algorithm. To implement the regulator and evaluate the cost function, neural network approximators were used. Spacecraft motion stability guarantees were obtained using the Lyapunov function method with account for the uncertainty in the spacecraft dynamics. The cost function was chosen as a candidate Lyapunov function. To simplify the stability test on the basis of this methodology, the dynamics of the plant was assumed to be Lipschitz continuous, which made it possible to use the Lagrange multiplier method for searching for control actions with account for the constraints formulated using the upper uncertainty bound and Lipschitz dynamics constants.

The efficiency of the proposed algorithm is illustrated by computer simulation results. The approach makes it possible to develop control systems that can improve their performance as data are accumulated during the operation of a specific object, thus allowing one to reduce the requirements for its elements (sensors, actuators), do without special test equipment, and reduce the development time and cost.

**Keywords:** *reinforcement learning, intelligent control system, spacecraft, stability, dynamic model.*

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