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Spacecraft attitude control using neuro-fuzzy approximation of the optimal controllers

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Abstract

In this study, a neuro-fuzzy controller (NFC) was developed for spacecraft attitude control to mitigate large computational load of the state-dependent Riccati equation (SDRE) controller. The NFC was developed by training a neuro-fuzzy network to approximate the SDRE controller. The stability of the NFC was numerically verified using a Lyapunov-based method, and the performance of the controller was analyzed in terms of approximation ability, steady-state error, cost, and execution time. The simulations and test results indicate that the developed NFC efficiently approximates the SDRE controller, with asymptotic stability in a bounded region of angular velocity encompassing the operational range of rapid-attitude maneuvers. In addition, it was shown that an approximated optimal feedback controller can be designed successfully through neuro-fuzzy approximation of the optimal open-loop controller.

Keywords: Spacecraft attitude control; Neuro-fuzzy network; State-dependent Riccati equation; Approximated optimal feedback controller

1. Introduction

Many nanosatellites are circulating around the Earth performing numerous valuable missions involving the testing of new space technologies. Utilization of groups of small satellites is becoming increasingly popular because of the low cost involved in their development and launching. Concomitantly, major possibilities exist for developing novel space technologies that enable multiple small satellite systems to perform as well as or better than single conventional large satellites. One of the significant limitations of small satellite systems, however, is that their computing ability is insufficient to handle complicated guidance, navigation, and control (GNC) algorithms. Although technologies are currently being developed to enhance the computing ability of small satellites, the heavy computational loads involved still render such systems costly in several respects. Consequently, there is a persistent need for simpler GNC algorithms with reduced computational burdens that are suited to the limited resources of small satellites.

The state-dependent Riccati equation (SDRE) technique has been used in numerous applications in the control field (Chang et al., 2009,2010; Abdelrahman et al., 2011; Abdelrahman and Park, 2011; Park et al., 2011). The SDRE control technique can be seen as a type of piecewise application of a linear quadratic regulator (LQR) because it calculates control signals at every time step by solving the algebraic Riccati equation in the same manner as an LQR. The SDRE controller is robust and yields a suboptimal solution for minimizing a cost function that contains both state error and control effort terms. One drawback of the SDRE control technique, however, is that the algebraic Riccati equation has to be solved for every sampling

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time, which consumes a significant amount of time to calculate a control signal.

An adaptive neuro-fuzzy system called the adaptive neuro-fuzzy inference system (ANFIS) was proposed by Jang (1993). ANFIS is based on a neural network and the first-order Takagi–Sugeno (TS) fuzzy model. The neural network provides the ability to learn from data, while the fuzzy model makes it possible to incorporate human knowledge in a systematic way. By combining the neural network and fuzzy model in such a manner that the parameters of the fuzzy network are adjusted by an appropriate learning algorithm, ANFIS is able to approximate any system whose mathematical model is unknown or difficult to obtain. The ANFIS proposed by Jang (1993) is trained by a hybrid learning rule that operates in a two-way sequence of backward and forward learning. In backward learning, the premise parameters are adjusted by a backpropagation algorithm, whereas in forward learning, the consequent parameters are updated by a least squares estimator (LSE). Several other training methods have been developed and applied to ANFIS, as described in the literature (Ghomsheh et al., 2007; Choi et al., 2007). Through the training process, the sum of the squared errors between the outputs of ANFIS and the target system is minimized, making ANFIS a universal approximator of any target system whose mathematical model is unavailable. ANFIS has been used extensively for parameter estimation (Tahmasebi and Hezarkhani, 2010), model prediction (Kurian et al., 2006; Aldrian and Djamil, 2008; Tektaş, 2010; Sivarao et al., 2009), and control (Mitra et al., 2007; Kabini, 2011; Jang and Sun, 1995; Lutfy et al., 2011).

Chen and Teng (1995) presented a model reference control approach that uses fuzzy neural networks (FNN). They used two FNNs: one for control (an FNN controller, or FNNC) and the other for plant identification (an FNN Identifier, or FNNI). The learning of the FNNC and FNNI was performed online via gradient descent (GD), with adaptation to system changes, and the convergence of the learning error was guaranteed by a Lyapunov function. However, the convergence of the learning error does not guarantee the convergence of the controller. Moreover, real-time applications may be infeasible because the online learning process is time consuming. Zhang et al. (2002) designed a neuro-fuzzy controller by training a neuro-fuzzy network using the training data obtained from a pro portional–integral–derivative (PID) controller and showed, through spacecraft attitude control simulations, that a neuro-fuzzy controller is more robust to external disturbances and dynamic uncertainty than a PID controller. Lakshmi and Nabi (2012) trained an ANFIS using spacecraft attitude and rate control simulation results based on a proportional–derivative (PD) controller. They compared their ANFIS controller to the PD controller in terms of control accuracy for a 10% uncertainty in the moment of inertia of the spacecraft, and showed that the ANFIS controller performed better than the PD controller. Also, Pelusi (2013) presented an algorithm for optimal selection of the training data which has much applicability in designing neuro-fuzzy controller.

The neuro-fuzzy approach can be used to overcome the drawbacks of the SDRE control technique. To solve the time-consumption problem associated with SDRE controllers, Kim et al. (2012) designed an ANFIS controller trained by an SDRE controller. They used subtractive clustering (Chiu, 1994) for initialization of the ANFIS to prevent an exponential increase in the number of rules with the number of states. The asymptotic stability of the ANFIS controller was analyzed using the Lyapunov approach. In an effort to reduce the computational load of the SDRE controller, Abdelrahman and Park (2013) proposed a hybrid controller in which a modified SDRE (MSDRE) controller is combined with an ANFIS controller trained by the MSDRE controller. They presented a Monte Carlo simulation to analyze the stability of the hybrid controller. The stability analyses presented in Kim et al. (2012) and Abdelrahman and Park (2013) were deemed insufficient for several reasons, as discussed in Section 4. Among the studies on designing controllers using neuro-fuzzy networks with the learning-from-data approach, apart from the work of Kim et al. (2012) and Abdelrahman and Park (2013), stability analysis of closed-loop systems is rare.

To design a more stable neuro-fuzzy controller (NFC) with better performance than the controllers developed by Kim et al. (2012) and Abdelrahman and Park (2013), a simplified NFC based on an SDRE controller was developed in this study and applied to the problem of spacecraft attitude and angular velocity control. The NFC was designed by training the adaptive parameters of a neuro-fuzzy network, based on a fuzzy model proposed by Kluska (2009), using the state-control data pairs of an SDRE controller. The fuzzy model is a zero-order TS fuzzy model with linear membership functions. The training data pairs were obtained through SDRE control simulations, using several different initial conditions, and had two inputs and one output, where the inputs were state error and the output was a control signal. In this study, the trained NFC was used to acquire the characteristics of the SDRE controller, such as suboptimality and robustness, while consuming much less execution time than the SDRE controller. The training algorithm used in this study to update consequent parameters with the premise parameters fixed was the recursive least squares estimator (RLSE) algorithm. A GD algorithm can be used in the training process to update the premise parameters. This GD algorithm operates sequentially with the LSE to minimize the training error. In this process, the training error is drastically decreased by one-time execution of the LSE and then gradually decreases by a small amount as a result of the effect of the GD. However, the smaller training error does not guarantee better performance of the NFC (Niestroy, 1996). Thus, in this study, the GD was omitted in the training process for simplicity of training. As a derivative-free global optimization technique, genetic algorithm (GA)