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Design and implementation of an adaptive critic-based neuro-fuzzy controller on an unmanned bicycle

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ABSTRACT

Fuzzy critic-based learning forms a reinforcement learning method based on dynamic programming. In this paper, an adaptive critic-based neuro-fuzzy system is presented for an unmanned bicycle. The only information available for the critic agent is the system feedback which is interpreted as the last action performed by the controller in the previous state. The signal produced by the critic agent is used along with the error back propagation to tune (online) conclusion parts of the fuzzy inference rules of the adaptive controller. Simulations and experiments are conducted to evaluate the performance of the proposed controller. The results demonstrate superior performance of the developed controller in terms of improved transient response, robustness to model uncertainty and fast online learning.

1. Introduction

Bicycle is an interesting vehicle due to its help in human health and environmental issues as well as being an exciting sport tool for many decades. Balancing a bicycle by a human driver is possible; however, stabilizing an unmanned bicycle is very complicated. The first step in this control synthesis is understanding the bicycle dynamics which is a complex nonlinear system. Attempts have been made to investigate both the dynamics and control. Schwab et al. presented several approaches such as pencil-and-paper, a numerical dynamics program, and a symbolic software to derive the linear motion equation of bicycle. This model has been a benchmark due to its accuracy [1]. Yavin [2] presented a nonlinear dynamic equation in which a simple structure of bicycle is used to develop equations of motion via the Lagrangian approach.

Different mechanisms have been applied to balance an unmanned bicycle which can be generally categorized in two groups, with or without stabilizer [3,4]. Hwang et al. applied two control strategies: first to control the bicycle center of gravity using an inverted pendulum and the second to control the steering angle [3] in which using two controller made the system more complicated. Chen employed an offline genetic algorithm to optimize the Fuzzy FIS (Fuzzy Inference System) membership functions in different forward velocities with handling of the steering angle [4].

The stabilizer based methods can also be classified into two groups: one using gyroscope (Control Moment Gyro (CMG) [5]) and the other inverted pendulum [6,7]. A CMG has a spinning rotor and one or more motorized gimbals that change the axis of rotor's angular momentum. Changing the angular momentum creates gyroscopic torque and makes the bicycle stable.

Lam and Sin utilized a gyroscopic stabilizer and implemented a PD controller to make a typical bicycle stable [6]. High energy consumption and their further weight are the main drawbacks of these kinds of control schemes. Moreover, it can only be used to stablize the bicycle with no ability to track a specific path. Inverted pendulum has been also used to move the Center of Gravity (COG) and make the bicycle stable [8].

Unmanned bicycle can also be made stable by controlling the torque exerted on the steering handlebar with an actuator [9,10]. Using this method, several control strategies have been used to stabilize the bicycle such as Fuzzy PID control [11], Fuzzy FIS [10] and Fuzzy sliding mode [3]. Considering the unstable nature of bicycle and the fact that the system is under-actuated, the controller designing for this system becomes a highly challenging problem. Summing up the conclusion reached by the previous works, the control of a bicycle's roll angle and steering-handle angle are two of the most important issues in realizing a stable running motion. Whereas, in the human ride bicycle, both of these aspects are elegantly accomplished by body control and thus achieving stable bicycle motion.

In this study, a critic based neuro-fuzzy controller is employed to stabilize and control the bicycle. Critic gives rewards and/or punishments with respect to the states reached by the learner.

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As critics constitute the less informative learning source, the learning methods using them represent very flexible tools [12]. These approaches, called reinforcement learning methods, consist of an active exploration of the state and action spaces to find what action to apply in each state [13]. This approach is also applied in other engineering areas; the authors in [14] employed the adaptive critic based controller to visually control a 7 DOF robot manipulator. This approach also used in [15] to tune steam generator water level.

We therefore focus on the design of this controller; a novel approach that can improve the transient response, robustness due to its model-free characteristic; the capability to adapt quickly with varying environment owing to learning ability. The main advantage of the proposed controller over previous fuzzy control approaches (e.g., neurofuzzy controller), is its online tuning characteristic by using a critic. That remarkably reduces the amount of computations used for parameter adaptation making it desirable for real time applications. This model free approach leads to a significant reduction in the computational burden as compared to model-based approaches, as well as existing learning approaches. The simplicity of the controller structure will make it attractive in industrial implementations where PD/PID type schemes are in common use [14]. In this reference, the computational load of this method and its convergence analysis by using direct method of Lyapunov method were studied.

The rest of paper is organized as follows. Next, a bicycle model is presented. In Section 3, adaptive critic based controller is introduced. The approach is then tailored for an autonomous bicycle in Section 4. Section 5 is dedicated to simulations, and Section 6 presents the experimental results. Section 7 concludes the paper.

2. System modeling

The equations of motion of a bicycle forms the system model. Here we take a dynamic model consisting two DOF with fixed forward velocity [1]. Inputs to the model are steering handlebar angle and roll angle which are shown in Fig. 1 $\left(q = (\phi, \delta)^T\right)$. In this model, the velocity of bicycle is also considered fixed.

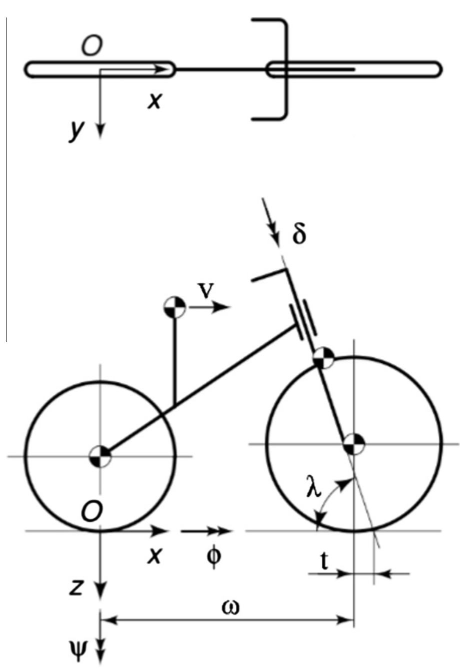

Fig. 1. Bicycle model with demonstrating the coordinate system, the degrees of freedom and parameters [1].

In Fig. 1, δ shows the steering angle, ϕ is the roll angle, ψ indicates the yaw angle and v the forward velocity of bicycle, assumed constant here. The bicycle's equation of motion is:

$$M\ddot{q}^d + [C \cdot v]\dot{q}^d + [K_1 + K_2 v^2]q^d = f^d \tag{1}$$

$$\dot{\psi} = \frac{v\delta + t\dot{\delta}}{\omega} \sin\lambda \tag{2}$$

$$\begin{aligned} \dot{x}_p &= v\cos\psi \\ \dot{y}_p &= v\sin\psi \end{aligned} \tag{3}$$

where M is the mass matrix whose elements are functions of components' mass and inertia, C is the damping matrix, K_1 shows the velocity-independent elements of the stiffness matrix and K_2 shows the elements of the stiffness matrix to be multiplied by the square of the forward speed. The last element, f, is the external forces $\left(f = (f_\phi, f_\delta)^T\right)$ including steering force applied to the handlebar and lateral force which can be assumed as a disturbance. Considering the bicycle riding whether by human or an intelligent system, the steering force can be a torque applied by a hand or an actuator. Considering the rolling constraints, the yaw angle ψ can be computed as a function of the steering angle, fixed velocity, and bicycle parameters [16]. λ refers to the heading angle shown in Fig. 1, it is called mechanical trail (i.e. the perpendicular distance that the front wheel contact point is behind the steering axis) and ω is the distance between centers of wheels. The above mentioned parameters are determined based on the size of bicycle used in our experiments as follows. The above mentioned parameters are determined based on the size of bicycle used in our experiments as follows [1]:

$$M = \begin{bmatrix} 1.43 & 0.18 \\ 0.18 & 0.08 \end{bmatrix} \tag{4}$$

$$C = \begin{bmatrix} 0 & 2.34 \\ -0.32 & 0.42 \end{bmatrix} \tag{5}$$

$$K1 = \begin{bmatrix} -32.53 & -4.3 \\ -4.3 & -1.6 \end{bmatrix} \tag{6}$$

$$K2 = \begin{bmatrix} 0 & 4.3 \\ 0 & 0.6 \end{bmatrix} \tag{7}$$

3. Adaptive critic-based neurofuzzy controller

3.1. Neurofuzzy networks

In this subsection, the principles of fuzzy system used here are introduced. An equivalent architecture is then formed that incorporates the fuzzy concept into an adaptive neural network. Generally, a fuzzy system consists of a fuzzification unit, a fuzzy rule base, an inference engine and a defuzzification unit. The fuzzy system can be viewed as performing a real (nonfuzzy) and nonlinear mapping from an input vector $X \in \Re^n$, to an output vector $y = f(x) \in \Re^m$ (n and m are dimensions of the input and output vectors, respectively). The interfaces between real world and fuzzy world are a fuzzifier and a defuzzifier; the former maps real inputs to their corresponding fuzzy sets and the latter performs in the opposite way to map the fuzzy sets of output variables to the corresponding real outputs. Two types of fuzzy systems are commonly used; Takagi–Sugeno–Kang (TSK) and fuzzy systems with fuzzifier and defuzzifier. In this work, we used the first type. The fuzzy rule base consists of fuzzy rules, which use linguistic If-Then statements to describing the relationship between inputs and outputs.