UNITECH 2020 GABROVO

INTERNATIONAL SCIENTIFIC CONFERENCE
20-21 November 2020, GABROVO

REAL TIME BICYCLE ROBOT BALANCE CONTROL USING MACHINE LEARNING

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Abstract

Classic control systems leave the place to artificial intelligence control systems. In this study, an exemplary system is realized. In this study, the balance control of a two-wheel bicycle system was carried out. The control process is first was realized by using the PID control algorithm. Angle, acceleration and motor control signals in this process were taken as training data and a training model was created. As a result of the training, the code produced for the machine learning algorithm was embedded on the control card. The control of new balance conditions was carried out in real-time with machine learning.

Keywords: Machine learning, PID, real time, balance control, Ensemble learning.

INTRODUCTION

Balance control is one of the main application areas of control systems. Studies on inverted pendulum control, ball and beam control, wheel pendulum control, steward platform, bicycle balance control example types continue to develop. Aim of this study, the balancing and control process of the bicycle robot was carried out using machine learnings.

During the bicycle robot balancing process, the system consists of a torque-generating pulley, DC motor that rotates the pulley, Arduino control card, motor driver and MPU 6050 gyro sensor, as shown in Figure 1.

Data for machine learnings were received in real-time via a bicycle robot. This data consists of the angle information generated by the MPU6050 sensor and the motor control signals generated to balance it. The proportional-integral-derivative (PID) controller is used to keep the system in balance without using the machine learnings method.

Machine learning is an artificial intelligence field that enables the system to create a model by using learning from past experiences and to make estimation against future situations[1]. Machine learning is used in many disciplines of our age. It provides convenience to devices and people in data analysis, decision making, estimation, conclusion and classification processes. The combination of machine learning and artificial intelligence with devices has enabled the creation of smart, self-guessing capable devices[2]. Today, many systems are used by making use of the capabilities of artificial intelligence. These abilities were used in this study to control the balancing system[3] [4].

SYSTEM AND DYNAMIC MODELS

The bicycle robot system consists of two parts. These parts are pendulum wheel and dc motor. In the control design, two variables are controlled. These are bicycle angle and wheel torque via dc motor. The dynamic model of the system is calculated by the Euler-Lagrange formula 1: Euler-Lagrange Equations (L) is a very useful method of extracting the equations of motion of the dynamic system. For the solution of the Euler-Lagrange equation, firstly there must be a difference in kinetic energy and potential energy[5]. The parameters of the system are shown in figure 2. The system model is specified in the equations below.

$$\mathcal{L} = T - V \tag{1}$$

T: Total kinetic energy of system
V : Total potential energy of system

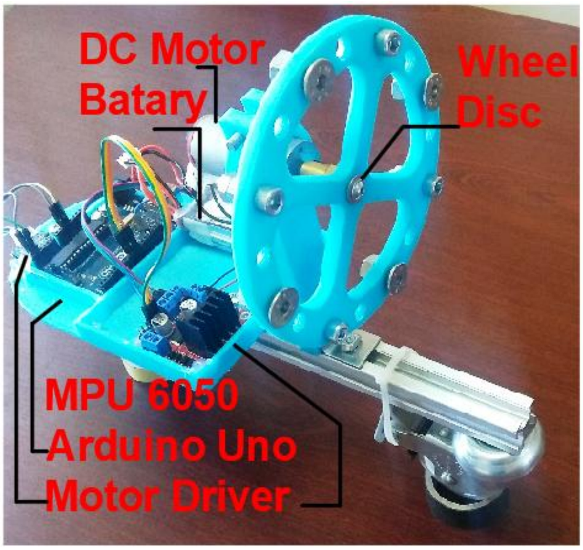

Fig. 1. *Bicycle Robot*

- *Mw* : Mass of the wheel
- *Mm*: Mass of the body
- *Iw* : Moment of inertia of Wheel
- *Im*: Moment of inertia of the body about the center of the robot
- *lF* : Distance between the center of the wheel and ground
- *lG*: Distance between the center of the robot body and ground
- *g: Acceleration of gravity*

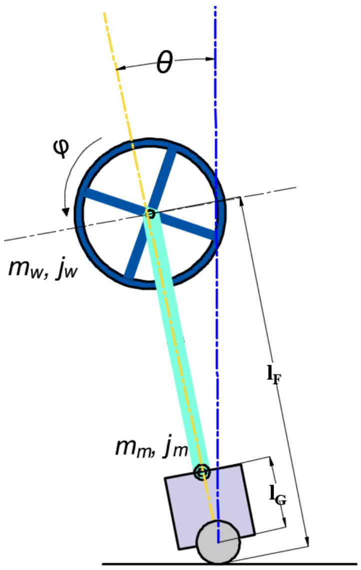

Fig. 2. *Parameter of the bicycle robot configuration*

The total potential energy and total kinetic energy of the system appears in eq. 2-3.

$$V = (m_w l_G + m_m l_F) g \cos\theta \quad (2)$$

$$T = \left(m_w {l_G}^2 + m_m {l_F}^2\right)\dot{\theta}^2 \quad (3)$$

The Lagrange difference equation appears eq. 4:

$$\mathcal{L} = (m_w l_G + m_m l_F) g \cos\theta - \left(m_w {l_G}^2 + m_m {l_F}^2\right)\dot{\theta}^2 \quad (4)$$

When the difference equation is written in the general Lagrange expression in 5

$$\frac{d}{dt}\left(\frac{\partial \mathcal{L}}{\partial \dot{\theta}}\right) - \left(\frac{\partial \mathcal{L}}{\partial \theta}\right) = T_G \quad (5)$$

where T_G denotes the reaction torque caused by the wheel. From equations(2-5), the dynamic equation is represented as equation 6.

$$\ddot{\theta} = \frac{(m_w l_G + m_m l_F) g \sin\theta}{2\left(m_w {l_G}^2 + m_m {l_F}^2\right)} + \frac{1}{2\left(m_w {l_G}^2 + m_m {l_F}^2\right)} T_G \quad (6)$$

After linearizing the system model of the bicycle robot in approximately θ~0°and θ' ~0 /sec, the dynamic equation of the system body can be expressed as equation 7.

$$\ddot{\theta} = \frac{(m_w l_G + m_m l_F) g \sin\theta}{2\left(m_w {l_G}^2 + m_m {l_F}^2\right)} + \frac{k_{torque}}{2\left(m_w {l_G}^2 + m_m {l_F}^2\right)} T_F \quad (7)$$

Where T_F is the torque generated by the wheel. The relationship between T_G and T_F can be expressed as $T_G = k_{torque} . T_F$ [6].

CONTROLLER DESINGN

The main purpose of the PID control system is that the controlled process variable reaches the target in minimum time with error. PID control compares the reference value and feedback variables. In order to eliminate the error between two variables, proportional, integral and derivative parameters are applied to the system. These parameters modify according to the system model. These Parameters are used in continuous cycling method and system response methods developed by Ziegler-Nichols. Large settling time and overshoot are minimized by Kp Ki Kd parameters[7][8][9].

Balancing control can be done by various methods. PID control system was used first for the control method with neural networks used in this study. Data on the PID control process were collected

In the control performed by machine learning, the data were classified according to the control structure performed with PID. The angle change and movement acceleration of the bicycle and the values of the pulse with modulation (PWM) signal produced for the DC motor were taken in real-time through the serial port. Since the PWM signals generated by PID change over time, the PWM signals are classified as 255-225-200-125-100-75. Generally, values between 75 and 125 produce a low amount of torque due to low speed and low-level balance distortion has been used. Values between 200 and 255 are used for fast and large balance changes. 3 * 10560 pieces of data were trained through MATLAB.

As a result of the training, the best training was achieved with Ensemble learning. Ensemble learning algorithms is a machine learning technique developed to increase the accuracy of classified systems. Classical machine learning algorithms normally predict using a single classifier. Ensemble Learning predicts more than one classifier[10]. As shown in figure 3. ROC curve and complexity matrix plots of the training can be seen in figures 4 and 5.

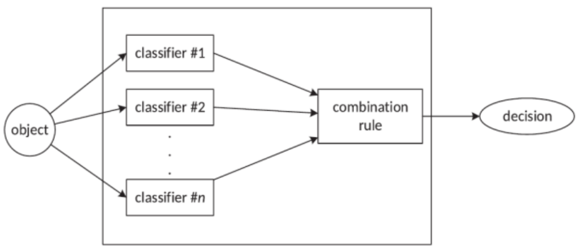

Fig. 3. Ensemble learning diagram

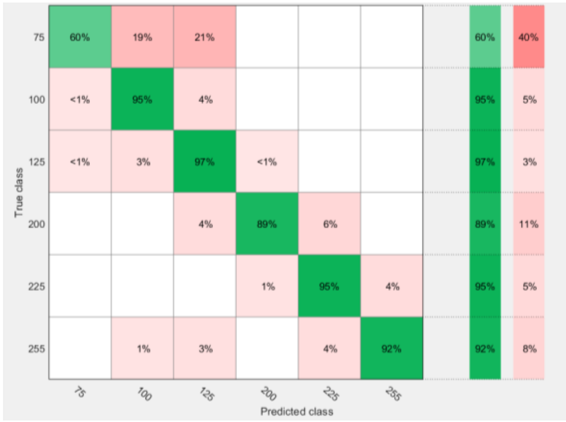

Fig. 4. Complexity matrix of ensemble learning

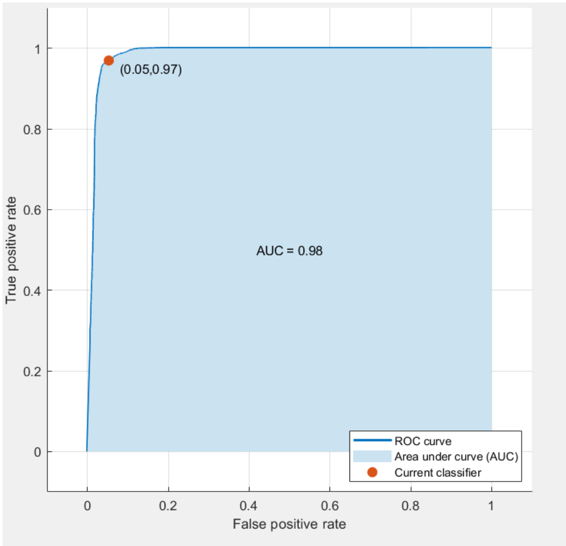

Fig. 5. ROC curve of ensemble learning

The C code of the training model obtained was produced and written on Arduino via MATLAB coder. The speed and direction of the motor were controlled according to the angle and acceleration information received from the robot.

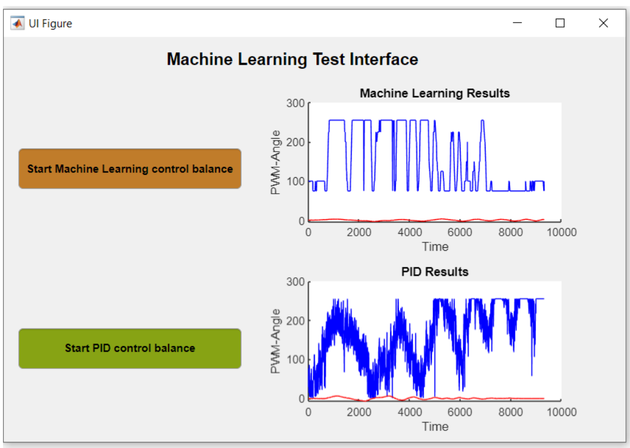

Fig. 6. PID and machine learning test interface

The data obtained can be seen in the app interface prepared in figure 6 and test analysis of different models can also be performed. It was designed that an app interface providing information on the differences, advantages and disadvantages on two different control type [11].

CONCLUSION

As a result of the work done, the balancing process was applied in both methods. PID control process analyzes and calculates fast and sudden emerging situations over time but may be delayed in response. In machine learning, the coefficients produced as a result on. In the real-time control made according to the training model, fast and sudden changes remained within certain limits.f the PID process was trained and classified. It was more efficient in machine learning signal in realizing the control response of the DC motor in motion. In summary, it has been observed in the study that the control effect of artificial intelligence on a real-time system is observed and the control over the systems is simpler.

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