School of Informatics

Informatics Project Proposal
Investigating Machine-Learning Oriented Self-Balance Control Strategy for Mobile Carrier Robot In ROS

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Abstract

The inverted pendulum system as multivariable, high order, nonlinear, strong coupling and naturally unstable system is a typical physical scenarios for testing the correctness of new control theory and algorithm. However, due to the constraint of freedom of vehicle motion, inverted pendulum balancing is difficult to be applied in a wide range of industrial scenarios,despite the fact that the feasibility and universality for these scenarios are constantly demanding. The proposed project aims to address these deficiencies by expanding scenarios to mobile robots with higher freedom of motion and exploring the possibilities of state-of-the-art machine learning control theory by simulation in ROS(Robot Operating System).

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Tutor: Mohammad Tahaei
Supervisor: Symons David

1 Motivation

The pole-balancing system, also called the inverted pendulum system(IPS) is a classic multi-variable, high order, nonlinear, strong coupling and naturally unstable system. In most case, inverted pendulum system is composed of a first-order pole and a bilaterally moving cart. This complex system is often used as a ideal self-balancing benchmark academic platform for testing whether the new control method has ability to deal with nonlinearity and instability. In recent years, with the increasing computer power, data-driven learning strategies including machine learning(ML) might in the future become the most modern method of doing IPS control[1][2][3]. The intuition of this strategy is to "learn" how to control itself by data and experiments without using classic control algorithm such as linear PID control. Besides, the research of this control method has been evaluated as the standard of the third generation robot: intelligent robot which has shown its great potential in the industrial field. For example, modelling the control problems encountered in the flight of rockets and missiles in the initial stages of launch[4] and the two-wheel inverted pendulum balancing vehicle which has been successfully commercialized[**?**].

Clearly, it would be best if the inverted pendulum system can be applied to any scenarios. However, the hypothesis is not valid because limitations on freedom and flexibility leads to this system too restrictive to model some scenarios, especially for those that the robot is required to do complex plane motion with higher degree of freedom to reach a target location and more flexible balancing demands. To solve this problem, the inverted pendulum model will be extended into possible application that moving items in a warehouse or having a robot waiter carry drinks without spilling them. However, complex physical properties are often required in specific scenarios which will be discussed in problem statement section in details.

The proposed proposal aim at systematacially reducing the above complex scenario to a novel benchmark inverted pendulum-like model with **more flexible movement and looser balance limits**. In addition, various ML methods, such as backpropagation and reinforcement learning will be applied into this benchmark to get further comparison for performance through the use of computational simulation.

The reminder of this section illustrate the details of problems, objectives and rationale for the proposed project. Section 2 outlines the knowledge and understanding of past and current work. Section 3 provides the details of methodology to be used to build benchmark and involved ML methods along with ethics and risk analysis. In Section 4, the methodology of data collection and evaluations will be discussed. Some expected outcomes will be listed in section 5 before the research plan, milestones and deliverables in section 6.

1.1 Problem Statement

This research can be considered as exploration research. As we discussed in section 1, the main purpose is to explore a machine learning method suitable for complex balance task on inverted pendulum-like robot model. After breaking the purpose down, there are three main problems and several corresponding sub-questions we need to explore.

Firstly, machine learning model can not be analyzed on nothing. In order to adapt to a wider range of scenarios, balance problem should be extended from classic inverted pendulum system. In section 1, we have briefly introduced the ideal scenario we are aiming to explore**(cargo robot in warehouse or waiter robot carrying a cup of water at the top of the robot without spilling them)**. However, as we mentioned above, this scenario involves complex physics properties which makes system more complicated, for example, it is extremely difficult to predict the exact state of liquid in real-time, because some complex variables such as viscosity, surface tension and dynamics equations of liquid should be considered. Also the influence of various shapes cannot be ignored, each of their fixed architecture determines limited application scenarios which makes the project too special. An more general architecture should be explored and built

This naturally raises a question, what kinds of general moving robot should be built. In other words, how to simplify the above complex scenario to get a more general and reliable robot system as a benchmark for exploration. Several possible design questions are listed below in details.

- How to simplify the object being moved?
- How to simplify the shape of the robot to adapt to different application scenarios?
- What kind of balance problem should we explore for the novel and more general carrier robot system?

This three possible design questions potentially can be solved by making several research hypotheses which will be discussed in section 1.2.

When a specific model is built, the choice of control algorithm is another core problem of our project. To solve this problem, some relevant questions should be considered as follows.

- How to set the state of "pole" unstable? Unstable state is the beginning of balance judgment which determines the potential speed and direction of the cart. Swing-up is a common strategy for classic inverted pendulum system to bring the pendulum from any initial position to the unstable position[5].However, an novel form of swing-up needs to be explored to fit the existing model. Some reasonable hypothesis about "swing-up" will be discussed in background section.
- In my expectation, we mainly discuss two different kinds of machine learning control on thus robot model which will be illustrated in the following section.
- Another question is how to evaluate the performance of different machine learning control strategies on thus novel robot system. For most of the traditional closed-loop control algorithms(a control relationship in which the controlled output returns to the control input in a certain way and exerts control influence on the control input)[6], **minimum variance control(MVC)** is a simple and reliable evaluation methods[7], using actual running data and a small amount of prior experience to estimate performance. However, when it comes to open-loop control, such as neural network control, some other evaluation methods should be explored.

1.2 Research Hypothesis and Objectives

This proposed project aims to investigate and evaluate the performance of various machine learning control algorithm on a novel carrier moving robot system with more flexible motion and strong balance. The first individual measurable objective is modelling. According to problem statement section, three potential barriers of designing this novel system are listed. Unluckily, from the relevant modelling literature I reviewed, there is no model that meets the requirements of this project. Therefore, to solve these questions, some reasonable research hypothesis should be made by our own to get more general system. This hypothesis can be easily described that a moving robot benchmark model mounting a hemispherical bowl, while a frictional ball move freely in the bowl. Following this hypothesis, the object being moved(liquid in previous example) has been simplified to a frictional ball planted in a a hemispherical bowl simplified from the carrier(cup in previous example). And this balance task can also be simplified and described as that explore a reliable machine learning algorithm which can keeps a ball within a hemispherical bowl mounted on the robot when it is moving.Beyond that, we need to make a series of assumptions about the properties of the model, the small ball, bowl and the cart are all rigid bodies; there is no relative sliding between the wheels and the ground directly; the driving force of the car is proportional to the input of the DC amplifier and there is no lag; the friction force of the car and the ball movement is proportional to the speed.

Another individual objective for this proposed project is to investigate the performance of various machine learning control in this benchmark model. And most of this work is in the intelligent control domain. In our expectations, reinforcement learning and a hybrid model of traditional PID**(Proportion Integration Differentiation)** control and machine learning will be explored. Among them, the achievement of neural network[1][8][9] will be considered as our minimum expectations. More details on the research programme and methodology will be discussed in section 3. In addition, it is well worth mentioning that our experiment results in simulation environment will be not applicable to real-world. Because as a more practical project, such questions in real-world are very specific, and this requests more sophisticated methodologies to consider the complexity and instability in real world.

1.3 Timeliness and Novelty

Our work is timely for the market. According to the latest industry analysis published by Juan et al.[10], the order quantity for professional service robots between 2018 and 2020 has increased by 300 percent compared to the number of orders in 2015. Also, there is a huge gap in demand for production-ready service robots in the next five years, which means the potential for commercialization of professional service robots is noteworthy. This proposed project, as a practical study on the balancing problem for service robots, is of great era significance and timeliness for promoting popularization of waiter robot. In addition, for the academic field, the inverted pendulum system, the most famous algorithmic test platform, is not suitable as the benchmark model for service robots, while in this proposed project, a novel benchmark system will be built based on IPS, which is specially designed for waiter robots in professional use.

Besides, in the terms of algorithm, most of previous work focus on the implementation of a single algorithm without comparing the differences between various methods[9][3][11]. Although comparing all methods is still out of scope, this proposed project will include the comparisons between traditional PID algorithms with at least one machine learning algorithms.

1.4 Significance

The originality of our work is demonstrated by ball-bowl benchmark model for waiter robot which has not been studied before. From the perspective of timeliness, this novel benchmark model has laid the foundation for the commercialization of robots which has been fully discussed in section 1.3. In the long run, this project provides a novel benchmark model for wider research. Insights into how state-of-the-art control algorithm perform in the future and how optimization problem be solved on this benchmark could accelerate the liberation of people's hands to achieve smarter intelligent robot.

1.5 Feasibility and Beneficiaries

This project is built on a ball-blow benchmark model extended from previously published inverted pendulum system. This benchmark model is novel because similar models have not been widely discussed in academia. Nonetheless the project is considered feasible, and this is supported by following factors. Firstly, the theory required for this project is similar to that of the inverted pendulum which has is been already well established in both industry[**?**] and academia[12]. Secondly, open-source code of various machine learning is available online and standard commercial laptop could support the calculation requirements of the project. Thirdly, as for feasibility of simulation, Gazebo[1], a toolbox for robot simulation in Robot Operation System(ROS)[2] can perfectly meet our needs.Also a low-cost moving robot called TurtleBot[3] is open-source in ROS community which can be considered as our our base robot in this project. More information about risk assessment and ethics can be found in Section 3.

The most immediate beneficiaries of the project are researchers who are devoted to balance problem of waiter robot. They can see the superiority from the comparison of the results in this project and in order for them to replicate this experiment or make improvements based on it, necessary code with detailed documentation will be open source to the public by Github, and some necessary summaries will be uploaded to the community.

2 Background and Related Work

According to the feasibility analysis in section 1.2 and 1.5, no studies were found to be based on the desired model for this project. However, as a variant of the inverted pendulum system(already discussed above), understanding how classic inverted pendulum system works and how various algorithms perform on it would be a good start for our project with heuristic.

2.1 Modelling

Modeling is the first step in the exploration of any control problem, this requires that the parameter relationships of the system during the motion should be indicated. The equation of dynamic motion for inverted pendulum can be derived from both Lagrange's equations and Newton's second law. The latter is highly recommended by Bellman and Richard[13] because forces could be revealed by Newton's second law including the reaction force between the cart and the pole. Nonlinear dynamics differential equations for IPS are as follows:

$$(M+m)\ddot{x} + ml\ddot{\theta}\cos\theta - ml\dot{\theta}^2\sin\theta = F \tag{1}$$

$$(I+ml^2)\ddot{\theta} + ml\ddot{x}\cos\theta - mgl\theta\sin\theta = 0 \tag{2}$$

[14] also emphasized that the cocal linearization process can be interpreted that the angle of the desired position (equilibrium point) is zero, which means the stable state of pendulum is around the upright position, following the modern control theory. To be more specific, $\sin\theta \approx 0, \cos\theta \approx 1$.

$$(M+m)\ddot{x} + ml\dot{\theta}^2 = F \tag{3}$$

$$(I+ml^2)\ddot{\theta} + ml\ddot{x} - mgl\theta = 0 \tag{4}$$

[1]http://gazebosim.org/
[2]https://www.ros.org/
[3]https://www.turtlebot.com/

Where m is the quality of pendulum, ℓ is the length of the pendulum, M is the mass of cart, F could be considered as the force applied to the cart by the motor.x'' is the acceleration of the cart, g is the standard gravity on the surface of the Earth. Using this method of linear approximation, complex non-linear IPS can be mathematically treated linearly using knowledge of linear systems which simplify the analysis process. For example, Choon et al.in [15] realized the linear PID control of inverted pendulum using this assumption, but the process of adjusting PID parameters is complicated and redundant. Bellman also illustrated that [16] in practice, the pendulum is easily disturbed by external factors that invalidate the linear impending assumption. Therefore, a control improved linear control method or different control methods based on nonlinear dynamic equations are needed.

2.2 Intelligent Control

Compared to both classical control theory which based on the transfer function and modern control theory which based on state space, intelligent control is more suitable for control of uncertain and highly nonlinear system [4].The idea of intelligent control emerged in 1971 by King-Sun Fu[17], he was the first to proposed the theory of binary intersection of intelligent control which incorporates the concept of AI into control theory.

2.2.1 Neural Network Controller

After that, with the rise of artificial neural network research in the middle of 1980s, researchers in the field of control put forward and rapidly developed neural network control methods which make full use of artificial neural network's good nonlinear approximation characteristics, self-learning characteristics and fault tolerance characteristics[18]. For example, in 1983, Barto[19] has designed two single-layer networks using adaptive heuristic critic learning algorithm to realize the inverted pendulum control of state discrete. In the next year, Anderson[1] has improved the number of layers of the neural network and used two two-layer neural networks as negative feedback circuits to realize the balance control of the inverted pendulum system without state discretization. However, Anderson[1] has also emphasized the lack of effective learning and data reliability when using neural networks for control. Therefore, at that time, researchers has been studying the feasibility of various machine learning control algorithm.

From now, many kinds of neural networks has been popularly employed in the control engineering. For example, Wang[20] has discussed the feasibility of various neural network based on Radial Basis Function(RBF) which contains the characteristic of the local regulation and overlapping of the receptive field to control. Besides, an adaptive PID neural network for complex control has been proposed by [21], this controller is for the situation that the use of simple PID controller tuning parameters is not ideal, which means the parameters of PID controller can be self-adaptive by BP neural network in Figure1. This approach is also one of the methods we need to refer to in our project.

In addition, evaluating the neural network controller is of great significance. In the simplest way, the performance could be evaluated through direct observation, the less time it takes to reach equilibrium, the better the controller, so other methods of controller as well. Another evaluation method for supervised neural network controller is to calculate the error between the output and the expected value using loss function.

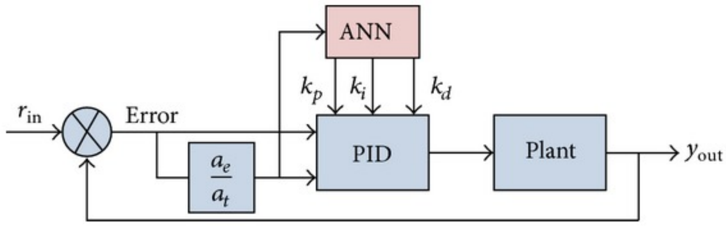

Figure 1: The structure diagram of the neural network PID controller proposed by [22]

2.2.2 Reinforcement learning Controller

Reinforcement learning, as a hot machine learning method in the academic circles in recent years, has also been actively explored in the possibility of its application in control theory. As a goal-directed computing approach, RL also allows the computer to make a series of decisions to maximize the cumulative rewards of a task without human intervention or explicit programming compared to methodology of neural network. In 1989 Wakins[23] firstly introduced reinforcement learning for solving Markov decision problems with incomplete information. In recent years,the combination of reinforcement learning and neural network has also become the mainstream direction, for example, Mnih, Volodymyr, et al.[24] introduced outstanding state-of-the-art reinforcement learning model in 2015 called Deep Q-Learning evolved from Q-Learning[23] by combining neural network and changing Q-table into Q-network, where many things that need to be paid attention to, such as the method of training DQN and the technique of combination. Considering time and workload of our project, DQN will be view as an possible extension of experiment, more details will be discussed in our future if time and workload permit.

3 Programme, Methodology and Evaluation

As we discussed in section 1 and 1.2, building a novel variant of inverted pendulum system and exploring the most suitable machine learning algorithm for controlling it are the high-level motivation of our project. To solve this problem, this project will be managed in several sequential steps. The details for them are as follows.

Existing Literature Review: Three key point will be collected in this step. Firstly, the process of modeling for control objects. Secondly, the transformation of nonlinear dynamic equations related to an inverted pendulum. Through similar transformation, we can finally derive the dynamic formula of this project model. Thirdly, how can machine learning algorithms be deployed in inverted pendulum systems, including training ML, evaluating and comparing.

Prepare the simulation environment: This step goes hand in hand with the first step which can also be considered as preparation. Robot Operation System(ROS) helps us to set up the environment that the project needs, including Robot simulation tool Gazebo, the Robit Visualization tool Rviz , also some lightweight tools such as rosbag for recording and playing back ROS topics, rqt for Structural visualization.

Build Robot Model: Having prepared relevant knowledge of ROS and reviewed argued literature and the hypothesis we made. Guided by this hypothesis, a novel robot model based on our hypothesis will be built in simulation environment. According to feasibility analysis in section

Risk	L	I	Management
Development environment failure	2	4	Build environment accordint to the tutorials on offial website, ask open-source community for help.
Invaild training data	3	4	Investigate the principle in details and ask open-source community and supervisor for help with questions.
General time pressure	3	4	Adjust the goal of project with supervisor.
Pessimistic results	3	2	Pessimistic results is possible,constructive advice should be proposed for further studuy.

Table 1: Potential Risks in the project

1.5, this targeted model can be made up of mobile robots(Turtlebot) and components(Ball and Bowl) which are all open-source code in ROS community and Github.

Improve the immature robot systems: The robot model that has been built so far has no interaction with the environment, improvements to this model need to be ongoing. Since no available data is directly used for the project, training and test data are better collected by ourselves. The controllability of the robot needs to be updated, this means our robot model is at least capable of controlling the direction of movement with a keyboard. For example, we can control robot to move by "QWEASDZXC" in keyboard. In this way, valid training data can be obtained.

Deployment algorithm on robot: Once we have collected sufficient training data, robot that keeps the ball in the bowl as they move will get smarter after deploying the algorithm. The deployed algorithm is neural PID algorithm[22][21] already discussed in section 2. Also, as mentioned in section 2, RL will be considered as our extension of this project, which could be explored if time permits.

Analyze results and make recommendations: Evaluation methods are various, in this project, the most easiest way is to observed whether the ball was successfully balanced. if it is successfully balanced, cost of balance time can be used as a standard for further evaluation. Based on that analysis, state experimental results, and possible improvements of this project will be proposed for further study.

3.1 Risk Assessment and Ethics

The major risk is listed in table 1, the L denotes the likelihood of occurrence and I denotes the impact of this risk. Both of them rated on range from 0 to 5, the higher the number, the higher the degree of this risk. Also, in this project, there is no ethics issue involved. Any data used in this project will be collected by ourselves.

4 Expected Outcomes

This project is expected to address the balance problem of a novel inverted pendulum-like system that can be considered as benchmark model for waiter robots from section 1. According to the hypothesis of this project, transforming from classic single-stage inverted pendulum to a new variant can show the originality of this project.

We expect that robots can reach equilibrium points faster and more robust controlled by neural

PID methodology compared to the classic PID algorithm. However, as a practical project based on a novel benchmark, obtaining a pessimistic results and outcomes are highly likely, which means there is a probability that we could get a negative performance on developed robot model. But this does not deny the significance of the project. Design structure of the model contributes to our understanding of how the dynamics of inverted pendulum systems can be derived through control process. This promises to provide important insights into the intelligent control process for complex system. In addition, pessimistic results often save the researchers the redundancy of repeating the experiment, which improves the efficiency for the exploration of optimal algorithm for this novel benchmark.

5 Research Plan, Milestones and Deliverables

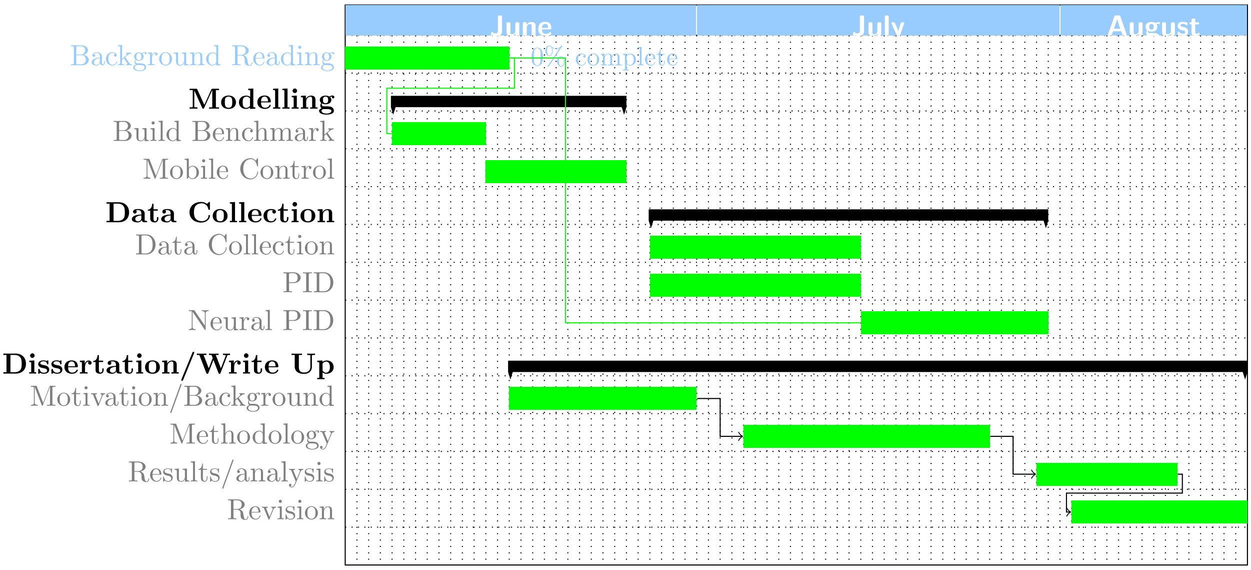

Figure 2: Gantt Chart of the activities defined for this project.

Milestone	Week	Description
M_1	2	Feasibility study completed
M_2	4	Initial benchmark design completed with mobile controller
M_3	4	implementation of traditional PID controller for benchmark
M_4	8	implementation of neural PID controller for benchmark
M_5	11	Submission of dissertation

Table 2: Milestones defined in this project.

Deliverable	Week	Description
D_1	4	implementation of novel robot model
D_2	8	neural PID controller for benchmark
D_3	11	Dissertation

Table 3: List of deliverables defined in this project.

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