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Project Proposal

Demonstrating Optimal Non-linear Temperature Control

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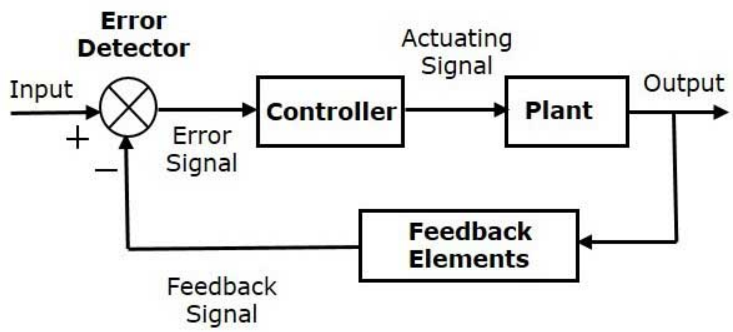

Figure 1: Block Diagram of a feedback control system. Source : Polytechnic Hub [4]

1 Overview

The existence of noise sources is unavoidable in any experimental measurement. These can always be minimized, but never eliminated completely. LIGO takes several measures to minimize noise at every point by maintaining an extremely low pressure vacuum, maintaining mirrors and other critical components at close to 0K etc. All of these efforts require the implementation of control systems to maintain a desired set-point irrespective of varying ambient conditions and noise sources.

A good example of this, which is similar to the system we wish to explore through this project is the thermostat. Once the user sets the temperature, a feedback control system ensures it is achieved and maintained by regulating the cooling/heating power through algorithms that take the error between present temperature and set-point temperature as an input. The control system aims to minimise this error and thus maintain the optimal state set by the experimentalist. Figure 1 shows the schematic of a general feedback system. In this example, the 'actuating signal' is the heating or cooling power, and the output is the current temperature of the room while input is the desired temperature.

Linear controllers, such as the ubiquitous Proportional-Integral-Derivative (PID) controller are among the most commonly used in a wide range of applications, from experiments to industries. This is due to their relatively simple yet effective control law that can be tuned easily to achieve desired characteristics. Simple PID control is an example of linear control, where the actuation signal is proportional to the signal obtained.

But linear control methods are not sufficient in many cases. These systems and their noise processes are inherently non-linear in nature, and it is often observed in such cases that the PID tuning changes if the set-points or any of the input variables are changed. For example, the problem of maintaining the temperature of an object is non-linear in nature, as the rate of heat lost to radiation is proportional to $(T_{\text{obj}}^4 - T_{\text{env}}^4)$, and if the set point is changed a simple PID would no longer work optimally.

An optimal control loop in a non-linear system would require the knowledge of the whole state space, where the actuation is not a linear and separable function of the system parameters. We aim to achieve this kind of adaptive control by utilising deep neural networks.

2 Objectives

We aim to demonstrate the advantages of non-linear control by experimentally implementing it to a classical but non-linear thermal system. This would consist of a mass composed of different materials that would have to be maintained at a set-point above the ambient temperature. As mentioned before, radiative heat loss makes this system non-linear and hence not ideal for controlling via a simple PID approach if we want to ensure it is effective over a large range of ambient temperatures.

Since tackling such systems analytically is very challenging, we will rely on neural networks trained over the parameter space using reinforcement learning (RL). This controller will mostly likely be in the form of a Raspberry Pi interfaced with a resistive heater that pumps heat into the experimental setup. This system is meant to be a simple demonstration of the effectiveness of such a method, but we ultimately hope this technique can be extended to quantum non-linear systems.

3 Approach

3.1 Modelling the system

We must first accurately model the heat transfer dynamics of a physical experimental structure located at Prof. Rana Adhikari's lab at Caltech. We must accurately take into account conductive and radiative losses to the environment of this cylindrical structure, taking into account the materials involved and their characteristics. This would be modelled in Python and must also be validated experimentally, since it is critical that the mathematical system matches the real one as closely as possible. This dictates the accuracy of the neural network based controller that we shall train.

3.2 Identifying NN architecture and RL strategy

We must next survey literature to understand how neural networks are exploited for non-linear control in similar situations. We must also study different reinforcement learning policies and techniques and decide suitable policies to train the network on the model of our system.

3.3 Hardware Implementation and Testing

Once this is done, the feedback system can be implemented on hardware and tested for robustness. This is the final goal of the SURF. We can also compare it with a simple PID controller and determine if there is a significant improvement.

4 Schedule

- **Weeks 1-3:** Examine the physical model and accurately represent it in code. Read up on neural networks and reinforcement learning policies
- **Weeks 4-5:** Simulate the response with PID control. Begin the training process after identifying which software package and training method to use
- **Weeks 6-9:** Implement the neural network based controller on a Raspberry Pi and work on the hardware setup
- **Week 10:** Compile results and work on completion of the final report

References

[1] This proposal is based on my online meetings with Prof. Rana Adhikari, Dr. Radhika Bhatt and Dr. Francisco Carcoba

[2] Shruti Maliakal, *Investigation of Optimal Non-linear Temperature Control*. LIGO SURF 2018 Proposal

[3] Andrei Diaconu, *Implementing Nonlinear Control in a Classical Experiment to Reduce Measurement Noise*. SURF 2023 Proposal

[4] https://www.polytechnichub.com/block-diagram-process-control-system/