Implementing Nonlinear Control in a Classical Experiment to Reduce Measurement Noise

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1. Introduction

All experiments in physics aim to measure some quantities that are then processed and analyzed in order to test a theory or to measure an unknown quantity. Hence, the precision of the measurement plays a crucial role in the quality of the result, so it is always desirable to reduce the uncertainty in the measurements that are being conducted. Advances in technology and physical theories have allowed the construction of experiments with unprecedented levels of sensitivity, but various background processes create noise that limits the sensitivity that can be achieved by our devices, especially in experiments working at quantum scales. To counterbalance this issue, modern experiments are built in order to reduce the effect of background noise sources (for instance, LIGO keeps it lasers in vacuum in order to avoid interactions with air molecules[1]), but no experiment manages to completely eliminate background noise (like quantum fluctuations).

The existence of noise sources has prompted physicist to implement control systems in their experiments[2]. Control systems actively alter the state of a device in order to maintain the optimal conditions for the experiment. Examples of control systems include thermostats that maintain a desired temperature or cruise-control systems in cars that maintain a desired speed. These control systems compare the value of the error in the measurement with a preset, optimal, value and then alter the system according in order to reduce the error. In effect, this is a feedback loop that takes in the signal (measured value) and feeds back the error into the system to bring it back to the desired state.

So far, most feedback loops have been modeled using functions that solve linear differential equations because there is extensive literature on how to solve such sets of equations, including frequency domain solutions using Fourier transforms. Linear control is also easier to implement since it requires little computation power and thus provides good feedback response times. Unfortunately, most background processes are nonlinear, so a linear feedback can only achieve a limited reduction in noise.

2. Objectives

The main objective of the project is to implement nonlinear control in a purely classical experiment. We think that nonlinear control could mitigate noise more effectively than linear control because nonlinear control covers a much broader family of control mechanism functions as opposed to linear controls which only cover functions that obey linear differential equations. In other words, linear controls assume that noise is linear, which is almost always false, or uses approximate linear solutions to model nonlinear noise which limits how effective the feedback system is at reducing noise. The solution would be to implement non-linear control in our experiments, but this was believed to be unachievable due to the complexity of the mathematical equations involved in modeling such systems. Unlike linear systems, only a narrow list of types of nonlinear systems can be solved analytically. However, we argue that some degree of nonlinear control could be achieved using an equivalent of a neural network using embedded quantum systems. Such a nonlinear control might be suboptimal, but it is likely to outperform linear controls which often rely on local linearization of the nonlinear system.

As proof of our concept, we aim to implement non-linear control in very sensitive seismometers that are already being used to measure fine movements of the earth and changes in its gravitational field. We will introduce the non-linear control using a computer with packages like Tensorflow, as a demonstration that non-linear control can be achieved in entirely classical experiments. The computer will control the temperature of the seismometer in order to reduce the noise at frequencies below 10 mHz which is caused by ambient temperature fluctuations.

If our classical nonlinear control is successful, we would want to reproduce our method in non-classical experiments by simulating the nonlinear quantum feedback in order to enhance a linear measurement device like LIGO, where noise suppression and coherence impose a hard limit on the experiment's capabilities. We will use packages like QisKit or Strawberry Fields to simulate the behavior of the interferometer with quantum feedback, and thus test if a nonlinear quantum control could be implemented in such experiments.

3. Approach

We will start by collecting a large amount of observational data from the seismometer. This data would include, but not be limited to motion measurements collected by the seismometer, the ambient temperature in the seismometer's housing, and the temperature of the seismometer itself. The more data we have, the more accurate our models for the noise can get by virtue of statistical inference. Then, we would want to eliminate any significant signals that might have been measured by the seismometer (i.e., actual earth movements or gravitational fields changes), and then create a data set consisting just of the background noise (and the accompanying temperature readings) for a long period of time. From there, we would train a convolutional neural network (CNN) on the noise data to see what is the correlation between ambient temperature fluctuations and the magnitude of the noise in the seismometer measurements. This CNN would then serve as a baseline for our control mechanism.

The actual implementation of the control will be achieved with hardware already installed in the seismometer assembly. However, we will adapt the control mechanism to be controlled by a computer running a neural network. A neural network (of any kind) would allow for creating a nonlinear response to the changes in ambient temperature or the signal from the seismometer because the activation functions (e.g., ReLU) introduce nonlinearities between the layers of the neural network. We aim to train our control neural network using adversarial training: we will monitor the performance of the neural network's control for some fixed amount of time and then adjust the parameters of the neural network in order to further reduce the magnitude of the noise. Along the way and at the very end, we will let the neural network run for longer periods of time (e.g., a few days) and train another CNN like the one above and compare the correlation between noise and ambient temperature fluctuations. Ideally, this correlation would be reduced and the overall magnitude of noise would decrease. If successful, we would like to make an estimate the improvement in sensitivity using the initial and final noise (and possibly their associated CNNs as well). This result would be of great interest to future calssical experiments that seek to incorporate a form of control feedback loop in order to further reduce the noise.

Lastly, we would like to explore the possibility of implementing such a non-linear control in quantum experiments. We are especially interested in the behavior of interferometers such as LIGO, due to their importance in the measurement of gravitational waves. To that end, we would simulate the quantum behavior of such an experiment using packages like QisKit and then train a neural network on the signal from the simulation in order to check if the noise in the measurements could be further reduced. It should be noted that even if our simulations indicate that nonlinear control could be achieved in non-classical experiments, this performance increase should also be tested in a real experiment, which could be an interesting topic for future research.

4. Work Plan

<u>Before the SURF</u>: Review existing papers on linear control, nonlinear control and familiarize with the experimental setup.

<u>Weeks 1-2:</u> Collect data from the seismometers, eliminate any signals from the seismometers and train a neural network on the noise measured by the seismometer.

<u>Weeks 3</u>: Implement the hardware required to control the temperature of the seismometer and connect said hardware to the neural network trained on the data from the first weeks.

<u>Weeks 4-7</u>: Improve the neural network using adversarial training in order to further increase the signal-to-noise ratio of the device.

<u>Weeks 8-9</u>: Model nonlinear control in quantum measurements using QisKit or Strawberry Fields, and check if nonlinear control could be achieved in an interferometer like LIGO.

Week 10: Interpret the results and identify methods of further improving the effectiveness of the quantum nonlinear controls.

5. References

1. Ultra-High Vacuum. *LIGO Lab | Caltech* https://www.ligo.caltech.edu/page/vacuum.
2. Feedback and Control Systems. *LIGO Lab | Caltech* https://www.ligo.caltech.edu/page/feedback.