Quantum Control using Machine Learning

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Abstract

Quantum control is an essential area of physics that helps in controlling the behaviour of open quantum systems, enabling the development of different quantum technologies. These tasks were previously treated as optimization problems, but recently, they have been approached using machine learning techniques.

In this project, I explored this field using reinforcement learning to perform quantum control and create a two-level quantum system. I designed a method that works with the density matrix of the two-level target states to find the best transformation parameters. These transformations can then be carried out using quantum gates, showing how reinforcement learning can make quantum control more efficient.

Quantum state

I worked in two-dimensional Hilbert space, using density matrix formalism. The target state density is:

$$\rho_{\text{target}} = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}.$$

Quantum channels

Depolarizing Channel:

$$K_0 = \sqrt{1-p}\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad K_1 = \sqrt{\frac{p}{3}}\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad K_2 = \sqrt{\frac{p}{3}}\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix}, \quad K_3 = \sqrt{\frac{p}{3}}\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}.$$

Amplitude Damping Channel:

$$K_0 = \begin{bmatrix} 1 & 0 \\ 0 & \sqrt{1-\gamma} \end{bmatrix}, \quad K_1 = \begin{bmatrix} 0 & \sqrt{\gamma} \\ 0 & 0 \end{bmatrix}.$$

Bit Flip Channel:

$$K_0 = \sqrt{1-p}\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad K_1 = \sqrt{p}\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}.$$

Quantum Measurments

Measurements are not completely projective, the operators are:

$$M_0 = \begin{pmatrix} \sqrt{1-\epsilon} & 0 \\ 0 & \sqrt{\epsilon} \end{pmatrix}, \quad M_1 = \begin{pmatrix} \sqrt{\epsilon} & 0 \\ 0 & \sqrt{1-\epsilon} \end{pmatrix}.$$

Control Model

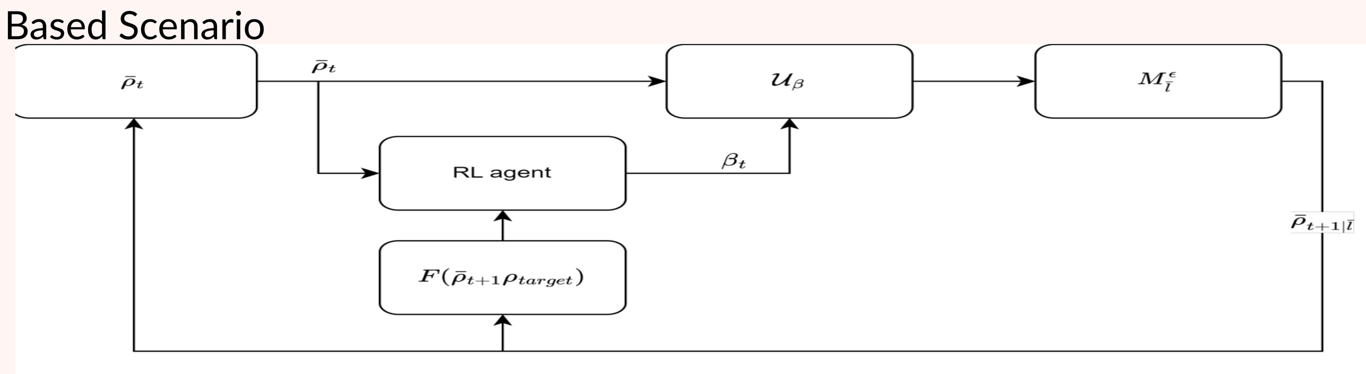
$$U_\beta(t) = e^{-iH_c(\beta_t)}, \quad H_c(\beta_t) = i\left[\beta_t\left(a - a^\dagger\right)\right].$$

where $\{\beta_t\}$ are the control parameters

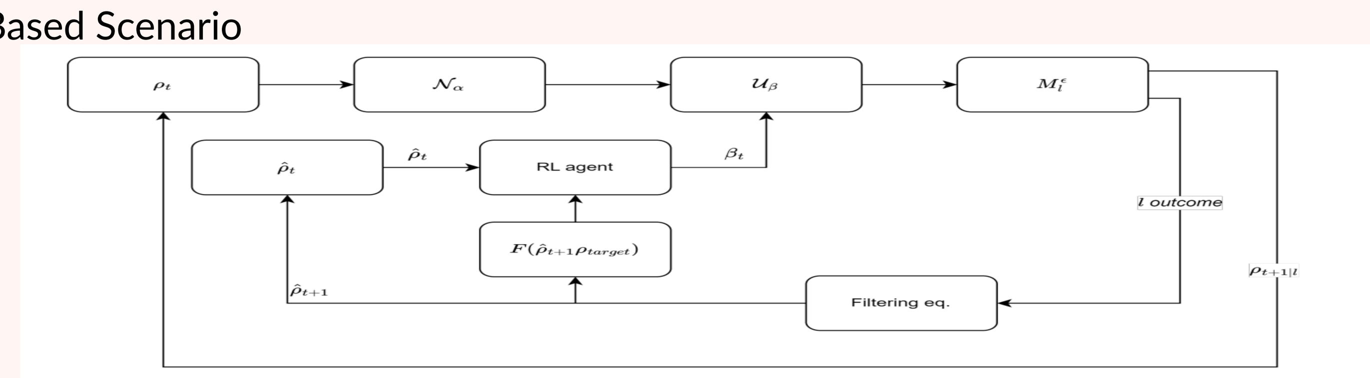
Learning models

I implemented two different models, each with its own limitations.

- Model Based Scenario



- Data Based Scenario



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Reinforcement Learning and Algorithm

Reinforcement learning (RL) is a machine learning approach where an "agent" learns to make decisions by interacting with an "environment". The agent takes actions in the environment, receives rewards or penalties based on those actions, and adjusts its behaviour over time to maximise its rewards. In the context of quantum control, the "environment" is the two-level system being controlled, and the "agent" is an algorithm attempting to learn optimal control parameters for the system. Policy gradient (PG): methods are a class of RL algorithms well-suited for quantum control problems.PG methods directly optimise the policy, which is a function that maps observations from the environment to actions. This is particularly advantageous for quantum control because:

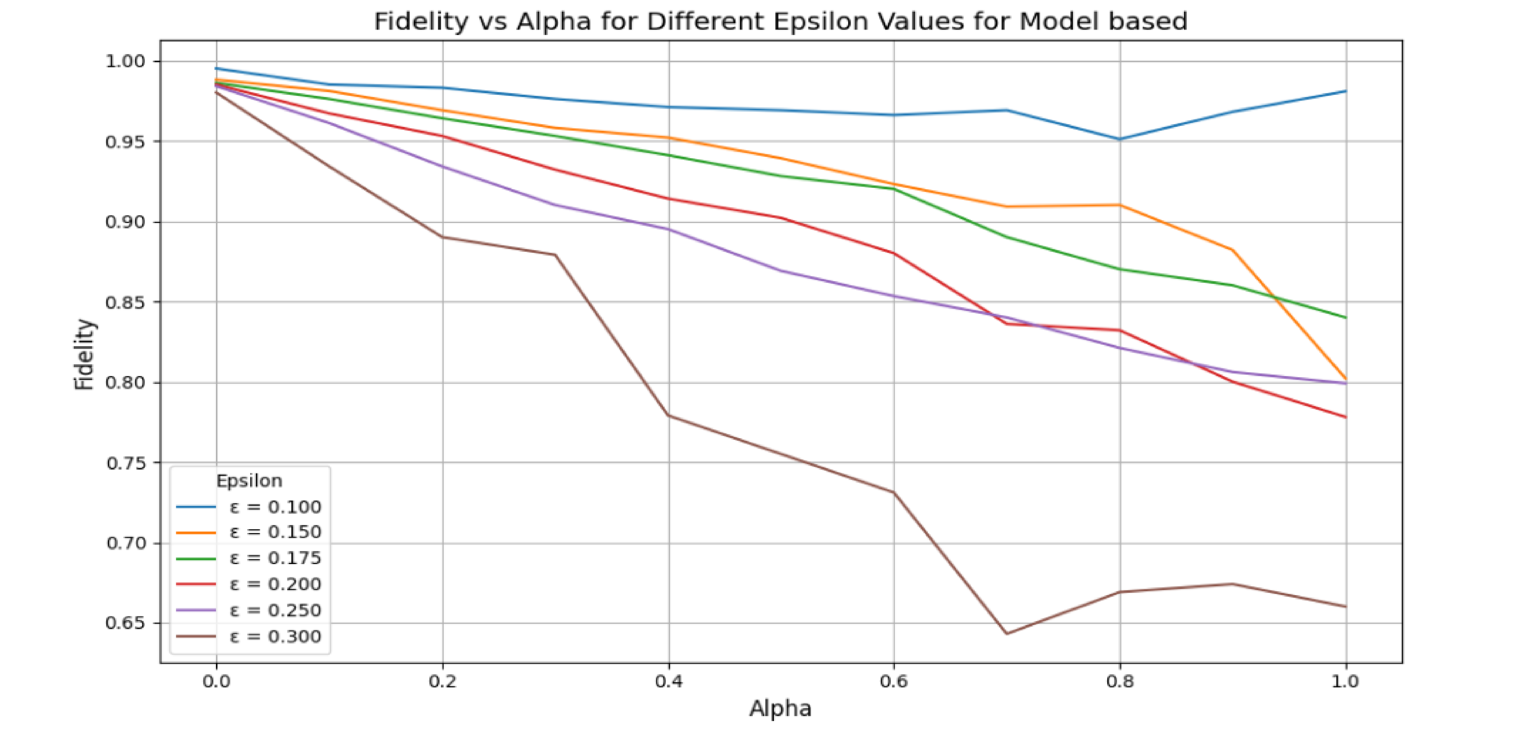
- Quantum systems have large continuous state spaces only partially observable through measurements.
- Policy gradient methods are more effective for continuous action spaces, which are common in quantum control.

The policy is represented by a neural network, with the network's weights and biases constituting the policy's parameters. The input to the network is the quantum system's current state (or observation), and the output is a probability distribution over possible actions (control parameters). The agent learns to adjust the policy parameters to maximise the expected cumulative reward over time. The learning process involves the following steps:

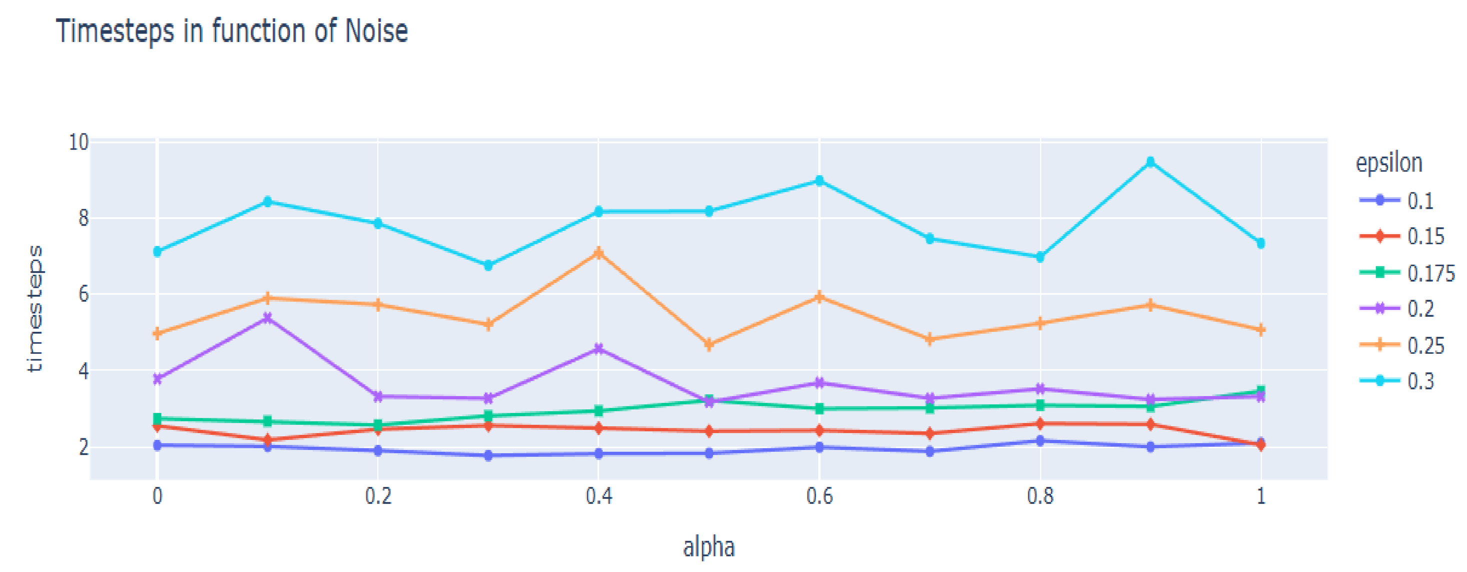
1. Interaction: The agent interacts with the environment by applying control parameters based on its current policy and observing the resulting state of the quantum system.
2. Reward Calculation: A reward function is defined based on the agent's performance. , different reward functions can be explored, including fidelity for a target state, alignment of measurement outcomes with a target state, and functions related to the Wigner function of the quantum state.
3. Policy Update: The agent updates its policy using a gradient-based optimisation algorithm based on the received rewards. Proximal Policy Optimization (PPO) is a standard algorithm that enhances learning stability by limiting policy updates within a trust region.

Results and discussion

Model Based



Data Based



Conclusions

- The DBS has less model bias and performs pretty well, even in larger noise and non-ideal measurements, giving fidelity up to 0.98.
- The MBS also performs well, but again, it is biased,I tried implementing a model-free algorithm, Where they don't explicitly define the Quantum channels, Model learn on their own. This is based on QODMP. The NN deciding the policy was based on LSTM, unlike in my case,MLP
- This framework can be implemented in different setups, too; even with this low dimensionality, it is a very general model that can be used for experiments for state generation, with few changes .

More exciting problems

- Setting up real experiments and building technologies using machine learning ideas, not just RL, but various approaches like PINNS, should be explored for various purposes.
- Using ideas from machine learning applied to the open quantum systems, we can reduce the model bias in our MBS, based system by accurately identifying the underlying master equation, i.e. the channels; but, applying these ideas has the limitation as the system gets complex we have limited experimental data as well as the simulations also gets fairly expensive, So proper budgeting should be done before, using these methods

Training Parameters

- **Batch size:** Set to 512 for each training update, representing the number of state-action pairs used to update network parameters.
- **Steps per update:** The agent interacted with the environment for 512 steps per training update.
- **Learning rate:** Set to 1×10^{-4}, controlling the step size during gradient descent updates.

References

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