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Optimal Quantum Control Using A Neural Network Ensemble

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1. Quantum Optimal Control

Optimal quantum control is fundamental for any quantum system to have a practical application. It presents itself as an optimisation task to maximise fidelity, the probability that a desired target state has been achieved, with respect to a set of control parameters. The variation of fidelity with a set of control parameters $\underline{\theta}$ is known as the control landscape $f(\underline{\theta})$. Our aim is to find a control solution to achieve the GHZ state, a maximally entangled state, given by

$$|GHZ\rangle = \frac{1}{\sqrt{2}}(|000\rangle + |111\rangle). \tag{1}$$

4. Method

Our ensemble consists of five networks, whose individual predictions and uncertainties are combined into one. The maximum of the surrogate model estimate and uncertainty is found and is explored during the next iteration. This allows the algorithm to efficiently explore uncertain areas of the control landscape until it converges on a optimal control solution. This process is displayed with respect to a GHZ control problem, in Figure 3, which is a benchmark for the implementation of our control algorithm.

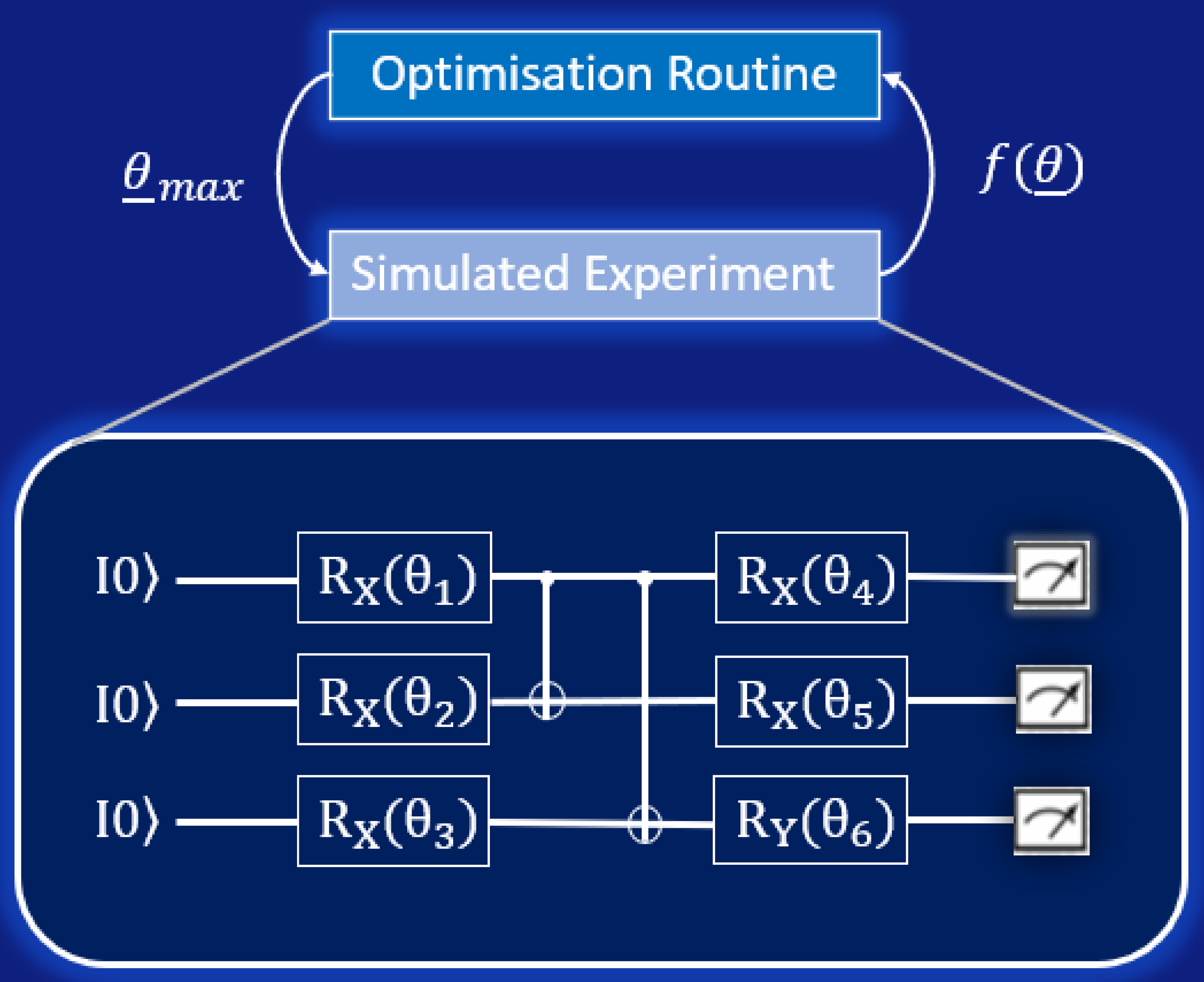

Figure 3: A quantum circuit to achieve a GHZ state from the ground state, integrated with the optimisation routine. Based on FIG. 3 from Sauvage and Mintert, 2020 and FIG. 1 from Pitchford et al., 2020.

Where $R_x(\theta)$, $R_y(\theta)$ refer to single qubit gates and two CNOT gates are also represented diagrammatically.

2. Research Objectives

Improve the scalability of an optimal quantum control solution with ensembles of neural networks and therefore make it applicable to more complex quantum systems.

3. Ensembles of Neural Networks

Bayesian optimisation provides efficient high quality solutions with poor quality data (Sauvage and Mintert, 2020). A surrogate model is used to approximate the underlying objective function, as shown in Figure 1.

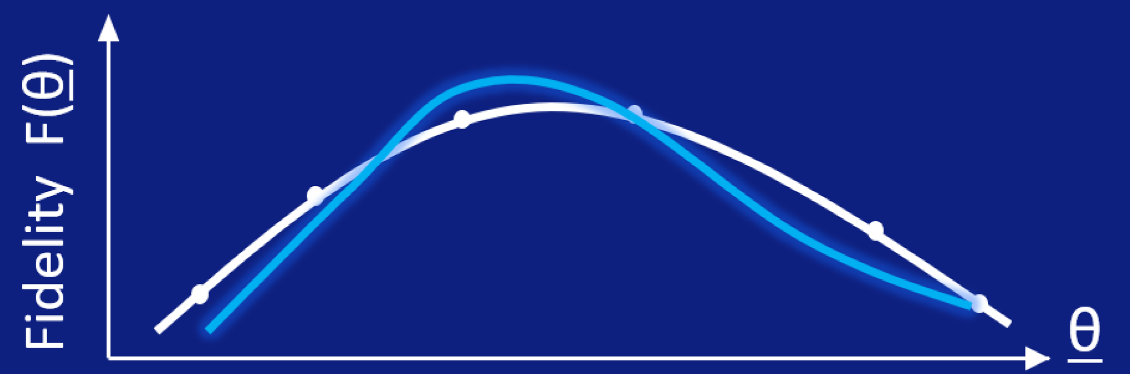

Figure 1: An example control landscape with discrete samples (white), the true objective function (white) and a surrogate model prediction (blue). Based on FIG. I from Sauvage and Mintert, 2020.

Gaussian processes, used to generate surrogate models, are cubic in complexity. Using a neural network ensemble instead would scale linearly (Snoek et al., 2015), to produce a control solution faster than a manual experiment for even more complex quantum systems. The neural network architecture shown in Figure 2 allows for both the prediction and the corresponding uncertainty of the surrogate model to be trainable.

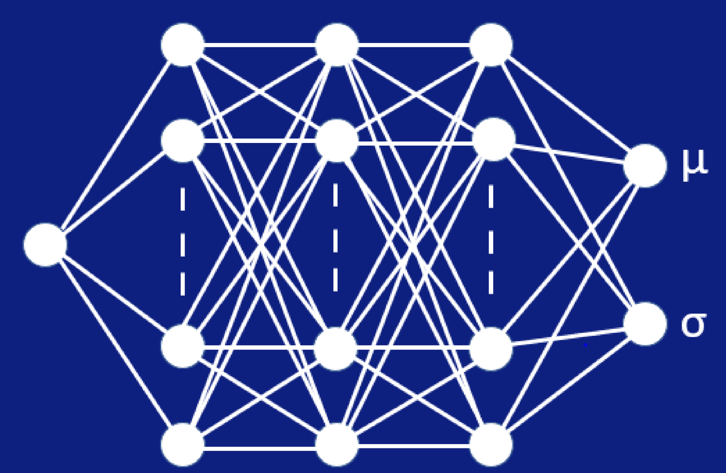

Figure 2: A neural network architecture which incorporates the prediction μ and uncertainty σ of the surrogate models. Based on Zychlinski, 2018.

6. Future Enhancements

Other enhancements include investigating the variation of performance with ensemble hyperparameters and exploring more complex quantum systems.

5. Preliminary Results

Measurements of a quantum system can take one of two values and with increasing repetitions, the recorded fidelity begins to reflect the true control landscape. 'Single-shot' ($N = 1$) data presents itself as the most complex task for surrogate model estimation and our results are shown in Figure 4 for a one-dimensional control problem.

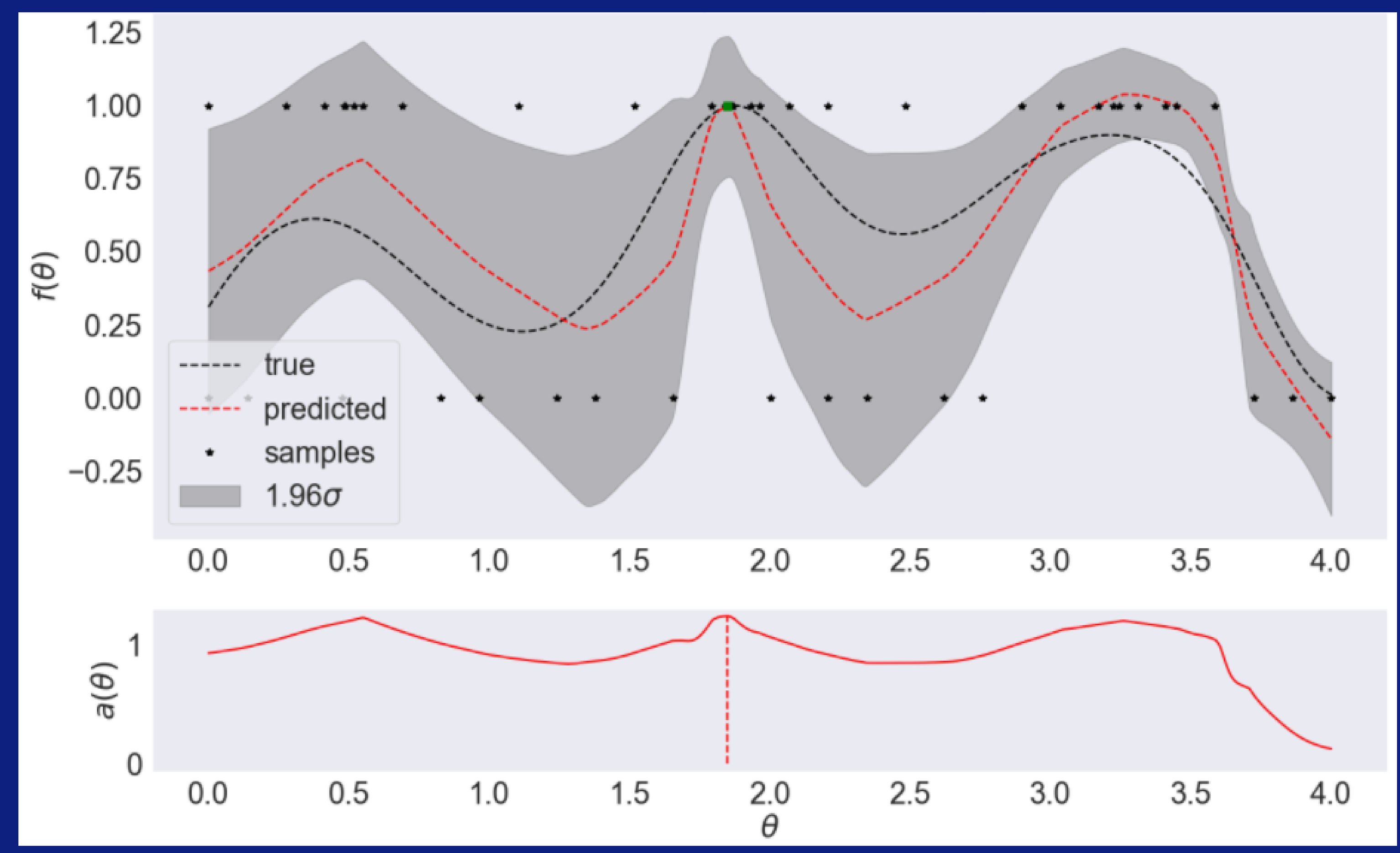

Figure 4: The estimated control landscape produced by the ensemble for single-shot data.

We can see that the routine has identified the global maximum and the surrogate model with its uncertainty encompasses the true landscape, shown in the first subplot of Figure 4. We can also see how the routine picks the next point to explore by combining the prediction and uncertainty, indicated by the second subplot. The next stage of our investigation is to join our optimisation routine with the output of our GHZ simulation.

Acknowledgements

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