Variational Quantum Regression applied to Computer Graphics

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1 Bidirectional Reflectance Distribution Function (BRDF)

In computer graphics, creating realistic images involves a process called rendering. A key ingredient for achieving this realism is accurately representing the materials that make up the objects in a scene. Materials have specific properties that determine how light interacts with them. In other words, how much light bounces off the material in one direction depends on the direction the light hit it from.

This complex relationship between incoming and outgoing light directions is captured by a special function called the Bidirectional Reflectance Distribution Function (BRDF). By understanding and incorporating BRDFs into rendering, we can create images that look incredibly lifelike

The BRDF takes into account the incoming light direction ω_i and the outgoing direction ω_r, returning the ratio of reflected radiance exiting along ω_r to the irradiance incident on the surface from the incoming direction. Each direction ω is given by two angles, $\theta \in [0, \frac{\pi}{2}]$ and $\phi \in [0, 2\pi]$, representing the elevation and orientation angles, respectively.

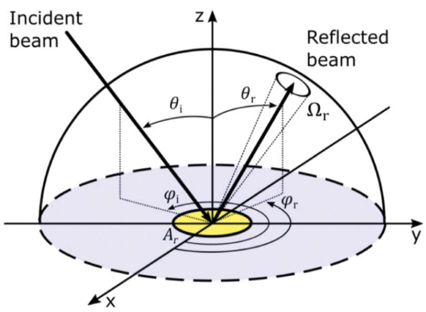

Figure 1: BRDF in an hemisphere

The simplest analytical models for BRDFs are the Lambert model and the Phong model, both shown in the following table:

BRDF	$f_r(\theta_i, \phi_i, \theta_r, \phi_r)$
Lambert	$k_d * \cos\theta_i$
Phong	$k_d * \cos\theta_i + k_s * (\cos(\omega_{\text{ref}}, \omega_r))^n$ with $\cos(\omega_{\text{ref}}, \omega_r) = \sin\theta_i \sin\theta_r \cos(\phi_i - \phi_r) - \cos\theta_i \cos\theta_r$

Table 1: Simple analytical models for BRDFs

where k_s, is a specular reflection constant (the ratio of reflection of the specular term of incoming light), k_d is a diffuse reflection constant (the ratio of reflection of the diffuse term of incoming light) and n is the shininess constant for the material.

In computer graphics, achieving photorealistic images relies heavily on accurately representing the materials that compose a scene. The BRDF plays a crucial role in this process.

However, simulating light transport through complex materials with traditional computers can be computationally expensive. Quantum computers offer a potential solution with their ability to perform calculations in parallel.

The aim of this project is to develop and assess a Variational Quantum Regression approach which can learn BRDFs, where the resulting model needs to be able to estimate the BRDF value of a given pair of direction (ω_i, ω_r).

2 DataSets

We chose the MERL BRDF Database[1], and selected a material, Tungsten Carbide, consisting of 1'480'000 measured samples of BRDF. It's important to note that the dataset utilizes a different parametrization for the vectors involved in the calculation, as shown in figure 2. As such we must reparametrize our pairs of incident and outgoing vectors in order to determine the BRDF.

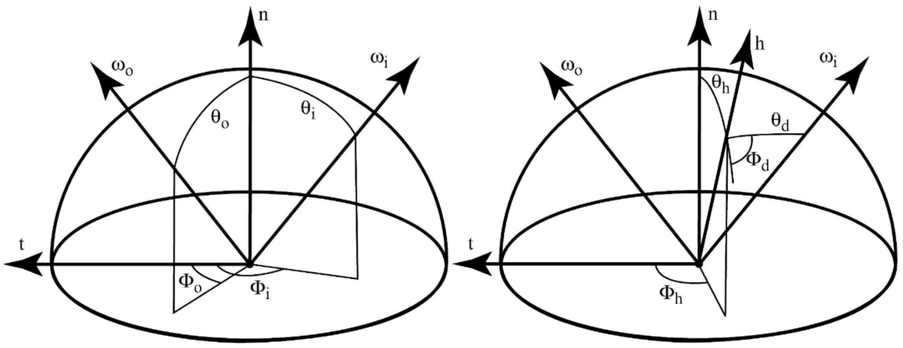

Figure 2: The standard coordinate frame is shown on the left. Rusinkiewicz's[2] coordinate system is shown on the right.

As such, the dataset utilized must be created by generating pairs of form (X^i, Y^i), where X^i represents an array of 4 different angles $(\theta_i, \phi_i, \theta_r, \phi_r)$, where, as described previous, $\theta \in [0, \frac{\pi}{2}]$ and $\phi \in [0, 2\pi]$ and Y^i represents the BRDF value present in the database.

The dataset must be posteriorly split into a training and a test datasets in rate between 60/40 to 80/20, where the training data will contain the the pair (X^i, Y^i), and the test dataset will only contain the (X^i) entry.

3 Methods and Results

In order to develop a variational quantum circuit the following approach must be followed:

1. Encode the classical data into a quantum state.
2. Design the ansatz that will be used for the regression.
3. Measurement of the results and classical post-processing.

Since we are not working with a classification algorithm, the results of applying the ansatz to the the circuit will be the value of the BRDF of the given pair. As such, the results will be evaluated by performing the absolute difference between the true value and the measured value, where *0* will represent a perfect classification. The absolute difference will represent the cost function of the model.

The ansatz must be trained with the main objective of minimizing the difference between the real value and and the value measured, always with the precaution of not overfitting the data.

In order to comprehensively evaluate the potential advantages of quantum variational circuits (QVCs), it's crucial to establish a benchmark using classical machine learning techniques. This involves creating and training another model:

- Classical Neural Network Regression: A neural network architecture suitable for regression tasks should be employed. This model will be trained on the same data used for the QVC.

By comparing the performance of both models on the regression task, we can assess the effectiveness of QVCs against a well-established classical approach. Specifically, we should evaluate metrics like prediction accuracy and generalization capability to a held-out test set. This comparative analysis will provide valuable insights into whether QVCs offer any significant advantages over classical neural networks for regression problems.

References

[1] Wojciech Matusik, Hanspeter Pfister, Matt Brand, and Leonard McMillan. A data-driven reflectance model. *ACM Transactions on Graphics*, 22(3):759–769, July 2003.

[2] Szymon M. Rusinkiewicz. A new change of variables for efficient brdf representation. In George Drettakis and Nelson Max, editors, *Rendering Techniques '98*, pages 11–22, Vienna, 1998. Springer Vienna.