Paper Reading Notes

Zhehao Yi

Contents

1   QNN-VRCS: A Quantum Neural Network for Vehicle Road Cooperation Systems

Date: September 15. 2025

Basic Info

- **Authors:** Nouhaila Innan, Bikash K. Behera, Saif Al-Kuwari, and Ahmed Farouk

- **Published in:** IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, 2025

- **DOI/Link:** `https://ieeexplore.ieee.org/document/10887095`

Summary

Vehicle Road Cooperation System means the real-time intersection between vehicle and road basic insturtion (traffic lights, monitors, sensors). But there are some problems in traditional VRCS, so far, VRCS depends on the heuristic methods (such as fixed-duration traffic light scheduling), but when facing dynamic and complex traffic flow, this method will go wrong, plus the coming 6G, the data between vehicles and roads will be larger (sensors, car networking), and traditional algorithms will struggle in terms of computational load and real-time performance. So this article proposed using Quantum Neural Network to solve VRCS problems.

They use three different encoding methord to generate quantum states (FRQI, NEQR, AE)). This article use two datasets, one is Carla (Simulated traffic lights), aother is Cropped Lisa (Real world traffic lights) to test the QNN. The results shows that when using carla dataset, QNN with AE encoding (Accurancy: 97.42%) outperforms CNN (Accurancy: 80% - 90%) for small inputs ($2{\times}2$), and when using Cropped Lisa dataset, QNN with AE encoding still performance the best, while other methods only made 43.33% - 77.09%.

Key Contributions

- A new QNN architecture is proposed and implemented specifically for VRCS.

- Evaluated the robustness of QNN under various noises

- Underscored the innovative role of QNNs in ITS, presenting a significant step toward embedding quantum-augmented intelligence in vehicular technologies.

Methods

Encoding

- Flexible Representation of Quantum Images (FRQI): Convert pixel grayscale to angle θ, encode into the qubits amplitude. $|i\rangle$ means associated pixel position encoding.

$$|I(\theta)\rangle = \frac{1}{2^n} \Sigma_{i=0}^{2^{2n}-1} (\cos \theta_i |0\rangle + \sin \theta_i |1\rangle)) \otimes |i\rangle \tag{1}$$

$$\theta = PixelValue \times \frac{\pi}{255} \tag{2}$$

- Novel Enhanced Quantum Representation (NEQR): Use a series of qubits to represent the intensity value of pixels presented by a set of CNOT gates. For representing two-dimensional images, we define the position of the image by its row and column, Y , X, respectively. 0 represents black, 1 represents white (Grayscale); Grayscale images with intensity values ranging from 0 to 255 are represented by 8 bits; color images are represented by 24 bits broken up into 3 groups of 8 bits, where each group of 8 bits represents the pixel color of red, green and yellow. pixel value:

$$f(X,Y) = C_{YX}^0, C_{YX}^1, ..., C_{YX}^{q-2}, C_{YX}^{q-1} \in [0,1], f(X,Y) \in [0, 2^{q-1}] \tag{3}$$

C is a binary representation. The general expression to represent an image for a $2^n \times 2^n$ dimension $|I\rangle$ is given as:

$$|I\rangle = \frac{1}{2^n} \Sigma_Y^{2^{2n-1}} \Sigma_X^{2^{2n-1}} |\otimes_{i=0}^{q-1}\rangle |C_{YX}^i\rangle |YX\rangle \tag{4}$$

n represents the size index of the image, q represents the number of bits required to represent pixel intensity. So the total number of qubits will be $2n + q$.

- Angle Encoding (AE):

$$\theta = \frac{\pi}{255} \times PixelValue \tag{5}$$

Classification

- $UU^\dagger$:

  - First choose a centroid of each image.

  - Build quantum circuit: U for centroid information (get $|\psi_i\rangle$), $U^\dagger$ for the test data (get $|\phi_i\rangle$).

  - Compute the inner product $\langle\psi_i|\phi_i\rangle$, compare the similarity between the sample and centroid.

  - The samples are classified into the category with the greatest similarity.

- Validate the classifications against actual test data to determine if the data corresponds to red, yellow, or green images

  - Compute the overall accurancy $c_1 N_1 + c_2 N_2 + c_3 N_3$. c_i represents classification accuracies for each color, N_i denotes the probabilities of these image categories (Number of specific images/ Total number of images)

- Variational $UU^\dagger$:

  - Almost than same as $UU^\dagger$, but add the Hadamard Gates

  - The expressibility of the circuit is good.

- Quantum Nerual Network:

  - Use AE to convert the pixels of the images into θ value.

  - Construction of quantum circuit.

    * Initialization the qubits.

    * Apply Rotation X gates.

    * Apply Entangle layer with Rotation Y and CNOT

  - Mesurement

  - MSE cost function

  - Optimization

Results

Personal Notes

Reference

Here is the reference paper [1]

References

[1] Nouhaila Innan, Bikash K. Behera, Saif Al-Kuwari, and Ahmed Farouk. "QNN-VRCS: A Quantum Neural Network for Vehicle Road Cooperation Systems." *IEEE Transactions on Intelligent Transportation Systems*, 2025, pp. 1–10.