3D-QAE: Fully Quantum Auto-Encoding of 3D Point Clouds

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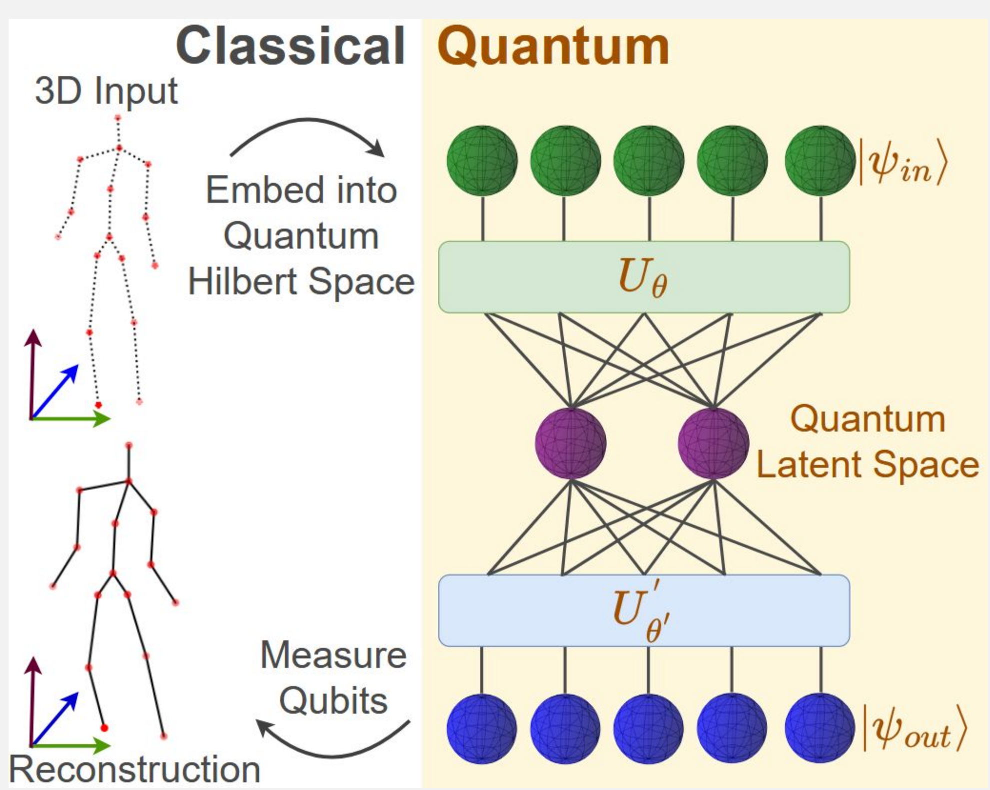
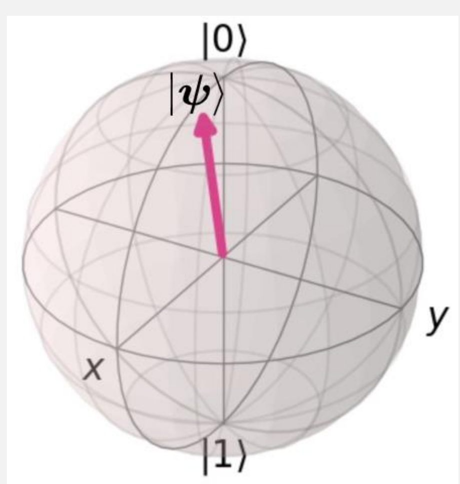
3D-QAE, a quantum point cloud auto-encoder. We prepare a classical 3D point cloud as input and then encode it into a quantum state vector $|\psi_{in}\rangle$ of two sets of qubits, A and B, via amplitude encoding. The encoder E (visualised here with J=1 block) acts on this state vector via a learned unitary transform implemented by a parameterized quantum circuit. At the bottleneck, we remove the information stored in the qubits B. This removal acts as a quantum nonlinearity whose output is the latent vector $|\varphi\rangle$ of qubits A. We re-initialise qubits B to $|0\rangle$ and let the decoder D, whose architecture is the same as E's, transform qubits A and B. We then measure the output of D to obtain the state vector $|\xi\rangle$, which we can classically process in a loss function or convert to the final 3D output reconstruction.

Motivation and Contributions

Quantum machine learning architectures (for universal quantum computers) have many theoretical advantages compared to the classical ones. Despite that, they have not been investigated for scene representation problems, e.g. auto-encoder training, involving 3D data (point clouds). This paper introduces introduces, i.e. the first fully quantum auto-encoder for 3D point clouds





The one qubit state: $|\psi\rangle = (-0.91 - 0.39\,j)|0\rangle + (-0.11 - 0.05\,j)|1\rangle$ on the Bloch sphere.

Contributions of this paper:

1. 3D-QAE, a fully quantum gate-based architecture for 3D point clouds auto-encoding,
2. Data normalisation scheme to make point sets compatible with quantum circuits, and
3. A quantum gate sequence for improved information propagation after the bottleneck.

The 3D-QAE Approach

Classical Input Data	x	y	z	$\sqrt{3-x^2-y^2-z^2}$
Normalisation	$\frac{x}{\sqrt{3}}$	$\frac{y}{\sqrt{3}}$	$\frac{z}{\sqrt{3}}$	$\frac{\sqrt{3-x^2-y^2-z^2}}{\sqrt{3}}$
Amplitude Encoding	$\frac{x}{\sqrt{3}}\|00\rangle + \frac{y}{\sqrt{3}}\|01\rangle + \frac{z}{\sqrt{3}}\|10\rangle + \frac{\sqrt{3-x^2-y^2-z^2}}{\sqrt{3}}\|11\rangle$			

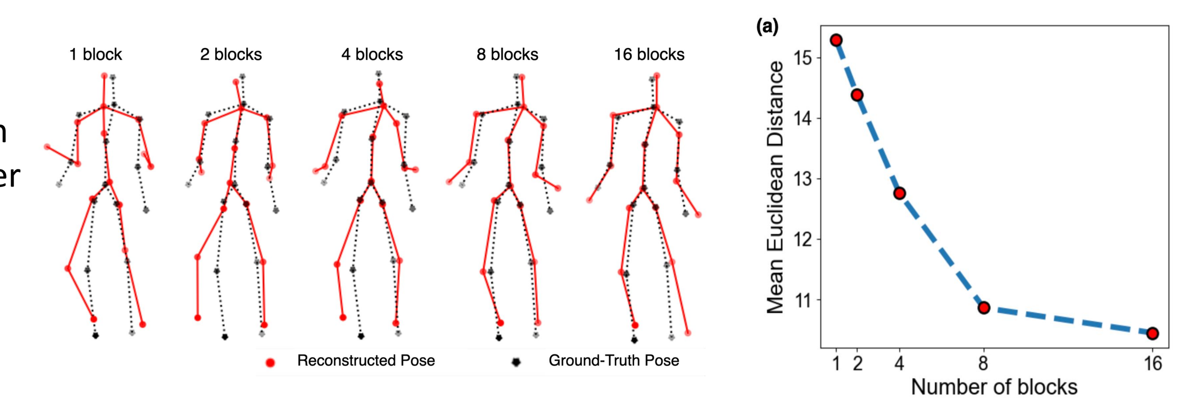
Data normalisation with Auxiliary Value

- The state vector after Amplitude Encoding must have a unit norm.
- To ensure that is the case, we also encode an auxiliary value: $\sqrt{3-x_i^2-y_i^2-z_i^2}$
- Now, we have unit-norm state vector:

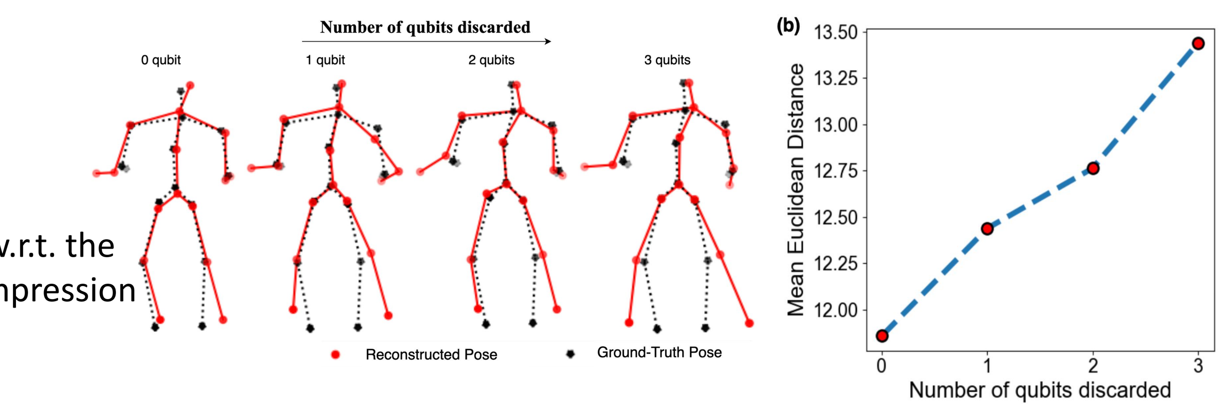
$$|\psi_{in}\rangle = \frac{1}{\sqrt{3V}}\sum_{i=0}^{V-1}\left(x_i|3i\rangle + y_i|3i+1\rangle + z_i|3i+2\rangle + \sqrt{3-x_i^2-y_i^2-z_i^2}\,|3V+i\rangle\right) + \sum_{j=4V}^{2^N-1} 0\,|j\rangle$$

Experimental Results

Do more quantum blocks mean better reconstruction?

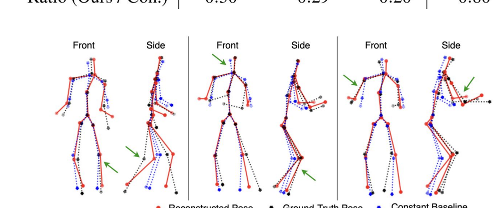


Performance degradation w.r.t. the degree of compression



Method	mean Euclidean distance
Constant baseline	13.58
Classical mimic baseline	3.75
Fully connected baseline (8 blocks)	8.37
Fully connected baseline (16 blocks)	3.85
Ours (8 blocks)	10.86
Ours (16 blocks)	10.45

Method	Left Leg	Right Arm	Spine	Full Body
Constant Baseline	10.7	22.1	7.4	13.6
Ours (8 blocks)	**3.2**	**6.5**	**1.5**	**10.9**
Ratio (Ours / Con.)	0.30	0.29	0.20	0.80



References

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Project page/source code:

Code