IQGAN: Robust Quantum Generative Adversarial Network for Image Synthesis On NISQ Devices

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Introduction

Quantum GANs

- **Data encoder $S(x)$**: Classical x → Q state $|\psi_\sigma\rangle$
- **Generator $G(\theta_g)$**: noise → Synthetic data $|\psi_\rho(\theta_g)\rangle$
- **Discriminator $D(\psi_\sigma, \psi_\rho)$**: Measure the fidelity between the real data $|\psi_\sigma\rangle$ and the fake data $|\psi_\rho\rangle$
- **Training Objective:**

$$\min_{\theta_g} L(\boldsymbol{\theta_g}) = \min_{\theta_g}[\mathbf{1} - \langle\psi_\sigma|\psi_\rho(\theta_g)\rangle^2]$$

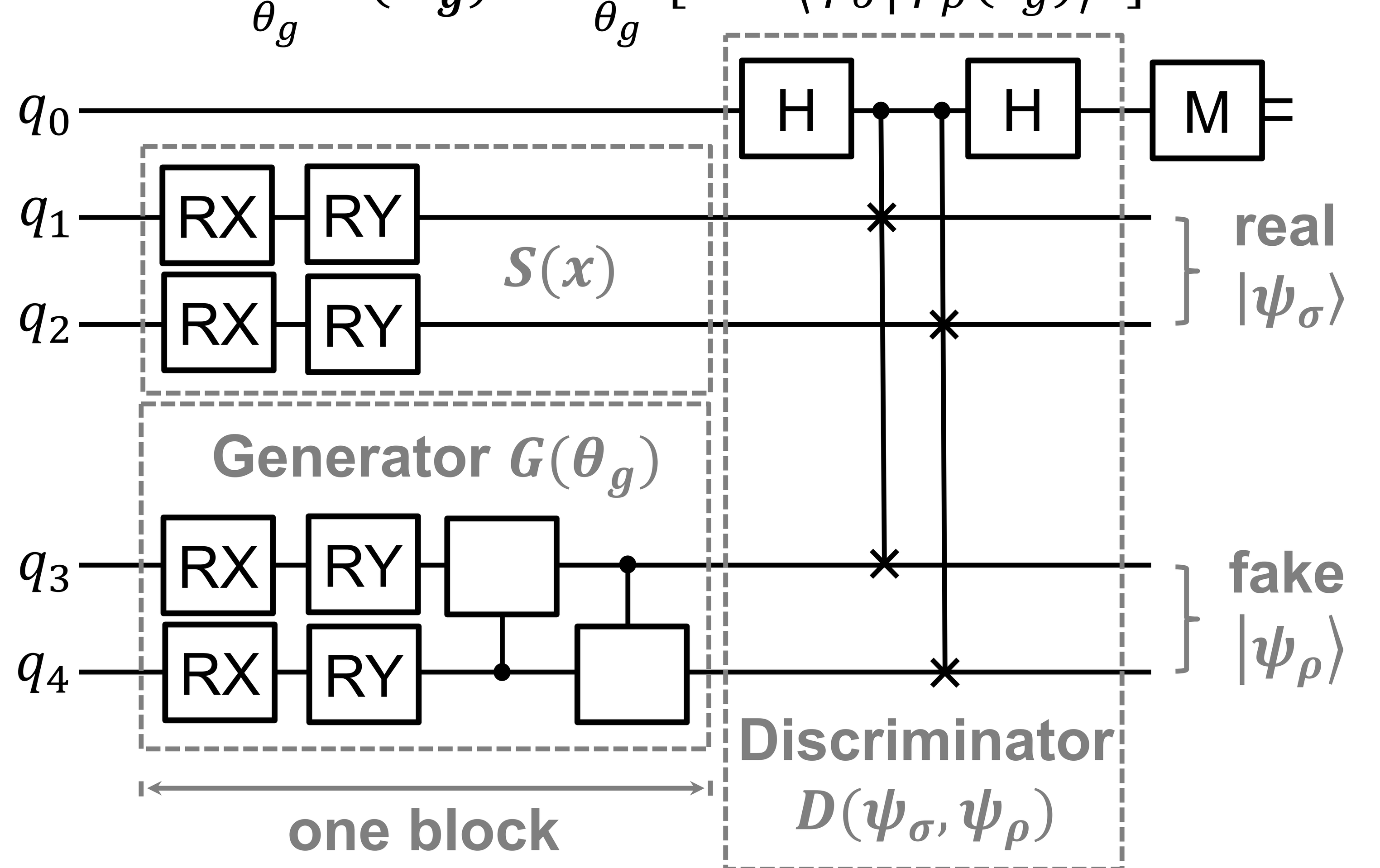

Fig.1 A standard QGAN

Motivation and Contribution

Contributions

- A trainable multiqubit encoder that achieved SOTA generative performance compared to prior works.
- A compact generator circuit ansatz.
- An efficient implementation of IQGAN on NISQ devices

Scheme	Loss	Conv.	MultiQ	Quality	Cost
QuGAN18[7]	Trace	×	×	Med.	High
QuGAN21[8]	Fidelity	√	√	Low	High
EQ-GAN[9]	Fidelity	√	×	Low	Med.
IQGAN	Fidelity	√	√	High	Low

Table1. Comparisons between IQGAN and previous works (Conv: Convergence; MultiQ: multiple-qubit output).

Methods

Trainable Multiqubit Quantum Encoder

- Variational encoder function $S(\arcsin(x * \theta_s))$
- Pre-trained param θ_s.
  - Pre-trained data set. $\mathcal{T} = \{(x_i, y_i)|0 \le i \le N-1\}$
  - Prepare quantum ensemble.
  - Train the $\boldsymbol{\theta_s}$ to maximize distance between $\boldsymbol{\sigma_{y_k}}$ and $\boldsymbol{\sigma_{y_m}}$, when $k \neq m$.

Compact Quantum Generator

- A generator w/o 2Q-Gate performs same as CRX and CROT with 6 × reduced hardware cost.

2QGate	Blck #	Cost	Fidelity	θ_0	θ_1	θ_2	⋯
CNOT	2	2.8×	0.813	N/A			
ISWAP	2	3.7×	0.954	N/A			
CRX(θ)	2	6×	0.969	-0.007	-0.023	-0.228	⋯
				0.003	0.036	1.799	⋯
CROT (ϕ, θ, ω)	2	6×	0.969	0.911	-0.057	2.049	⋯
				0.079	-0.086	-0.068	⋯
w/o	N/A	1×	0.969	N/A			

Table2. Comparison on quantum GANs with different 2Q-Gates.

Hardware Implementation Cost

Scheme	Qubit#	1QG#	2QG#	Param#
QuGAN21[8]	$2n+1$	$nb+1$	$4nb$	$5nb$
EQ-GAN[9]	$2n+1$	$2nb+n+2$	$(b+1)n$	$2nb$
IQGAN	$2n+1$	$2nb+n+2$	n	$2nb$

Table3. Hardware cost of different quantum GAN schemes (n: input size; b: repeated VQC block number; 1QG#/2QG#: one-/two-qubit gates number; Param#: parameter number).

Limitation and Scope

- Proved Quantum GAN advantages in [6].
- We focused on the situation where data is classical while the generator and discriminator are quantum.
- We implement small-scale IQGAN on MNIST.
- Implementation scale will improve with technology advancement.

Results

Effectiveness of the trainable encoder.

Task	Input Size	Qubit #	Accuracy (%)	
			FE	TE
MNIST-2	4*4	16	89.5	**90.9**
MNIST-4	2*2	4	43.2	**45.6**
MNIST-4	4*4	16	45.9	**49.4**
MNIST-8	4*4	16	23.25	**24.3**

Table4. Accuracy comparison of Fixed Encoder (FE) and Trainable Encoder (TE) on different subsets of MNIST.

Comparison of Image Quality

Fig.2 Comparison on image quality.

Convergence

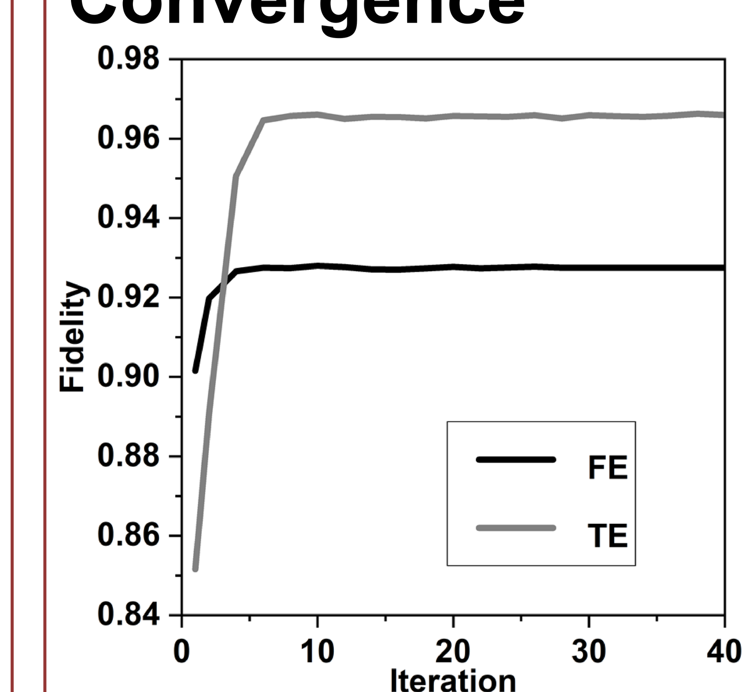

Fig3. IQGAN convergence.

Impact of noises.

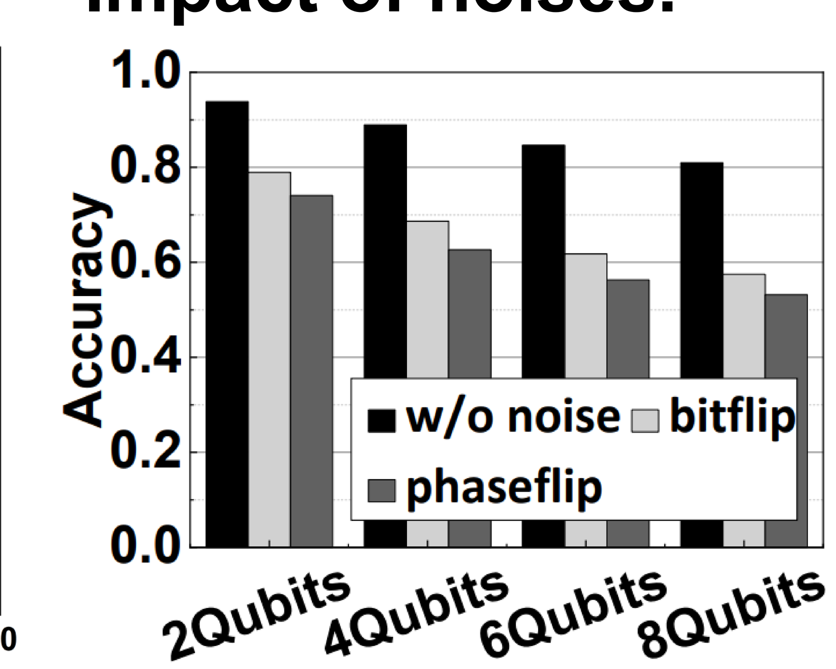

Fig4. IQGAN accuracies.

Conclusion

We propose IQGAN for image synthesis that can be implemented on NISQ devices. Results on both IBM quantum processors and simulators demonstrate that IQGAN outperforms the state-of-the-arts QGANs in image quality, model convergence, and required quantum hardware implementation cost.