Quantum Annealing for Single Image Super-Resolution

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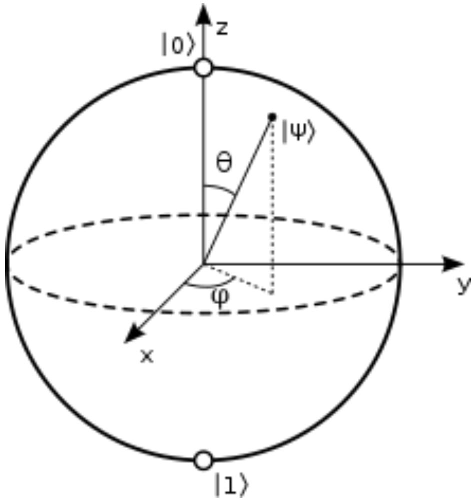
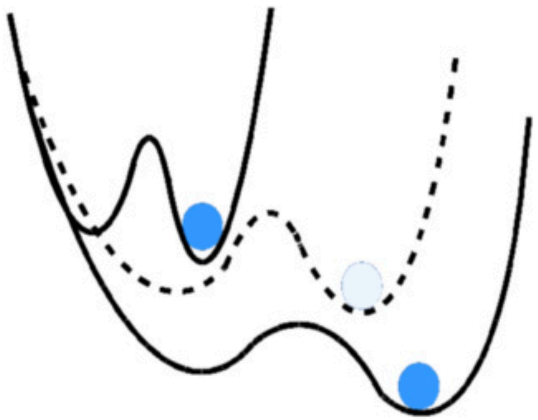
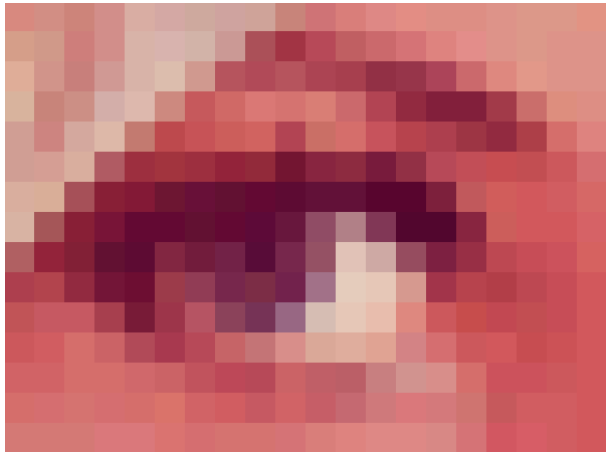
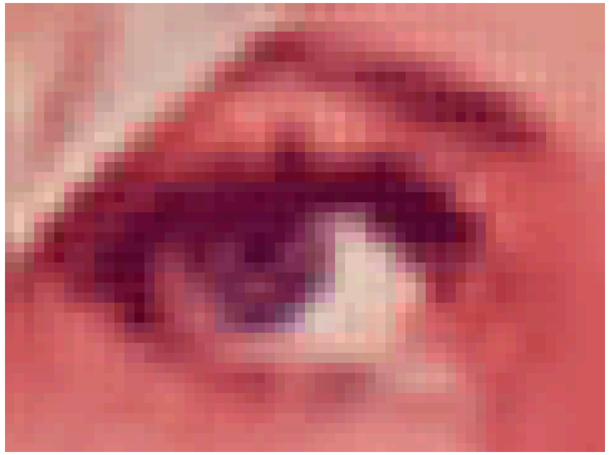
NTIRE 2023: CVPR 2023 New Trends in Image Restoration and Enhancement Workshop



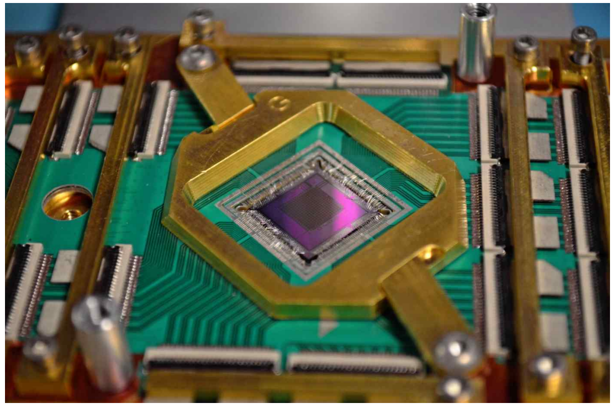




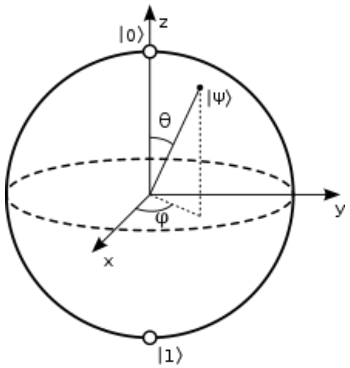


Overview

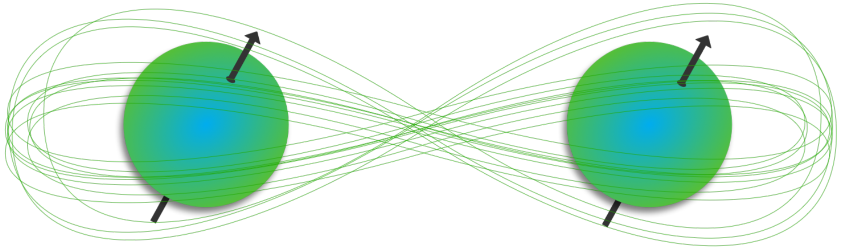
- Our work is an early exploration of applying quantum computing to single image super-resolution (**SISR**).
- Adiabatic quantum computing (**AQC**) can solve combinatorial optimization with exponential speed-up.
- Our approach uses a quadratic unconstrained binary optimization (**QUBO**) formulation for sparse coding.
- Evaluation on popular SISR datasets.



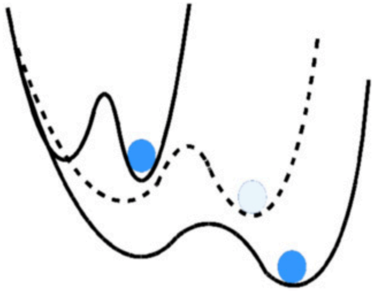
A quantum processing unit (QPU)



Superposition



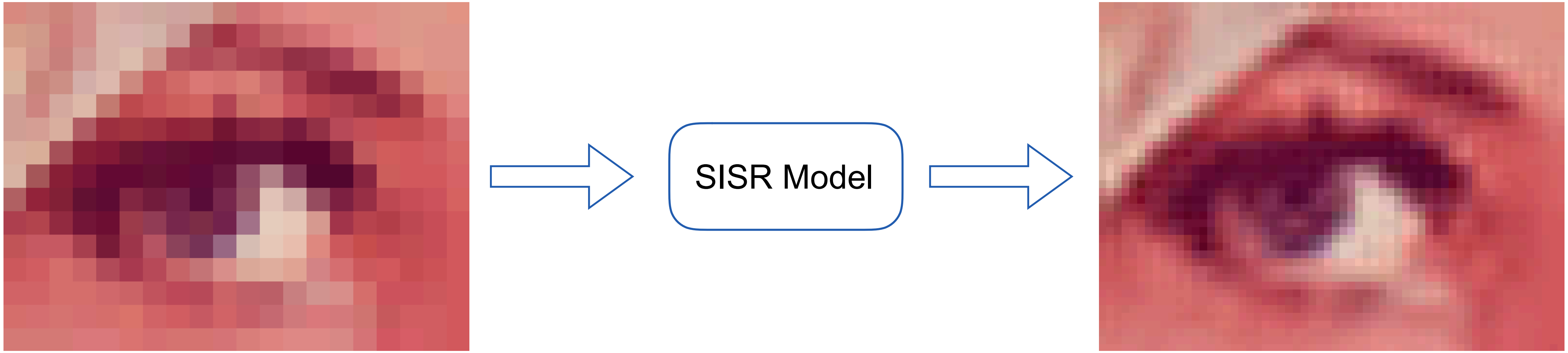
Entanglement



Adiabatic Evolution

Single Image Super-Resolution

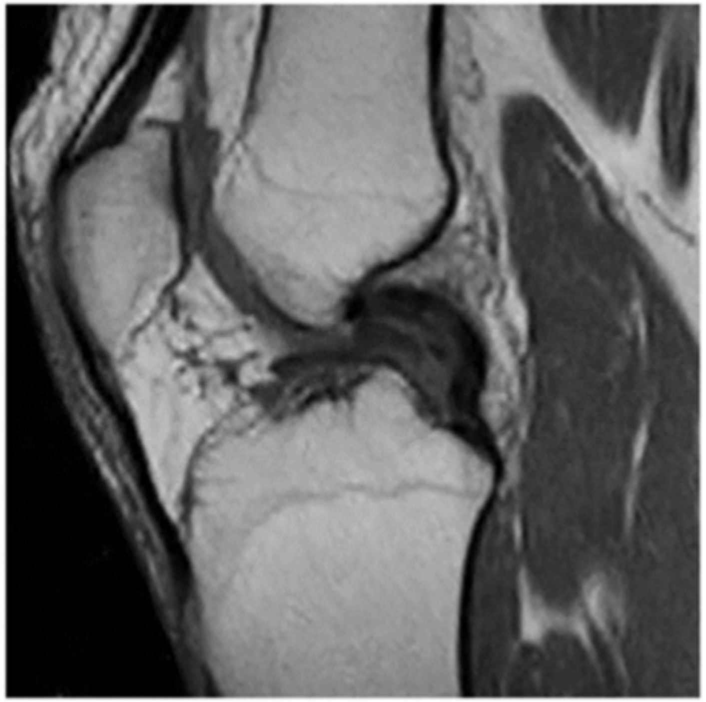
Single image super-resolution (**SISR**) is the problem of reconstructing a credible and visually adequate high-resolution (HR) image from its low-resolution (LR) image representation.



LR HR

Applications of SISR

Applications in medical imaging, remote sensing and scientific research.



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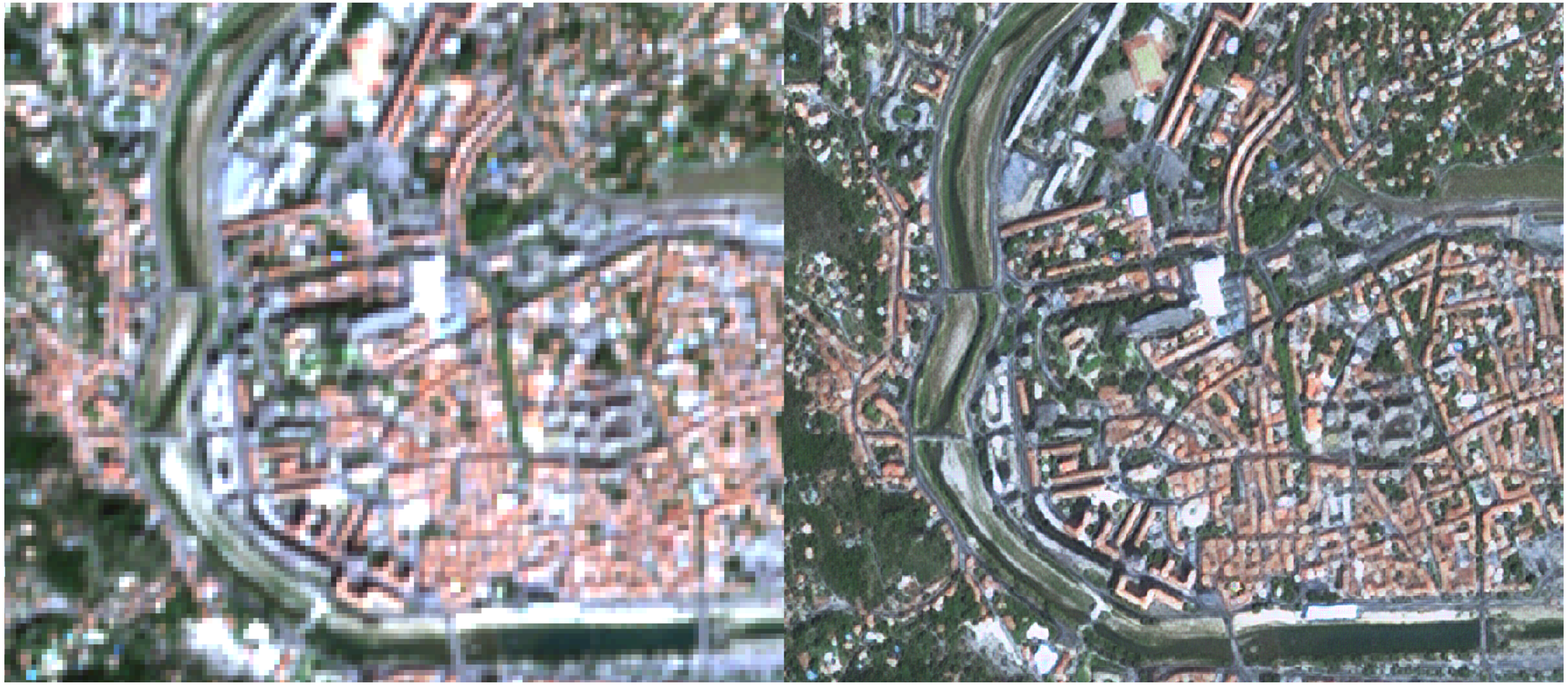

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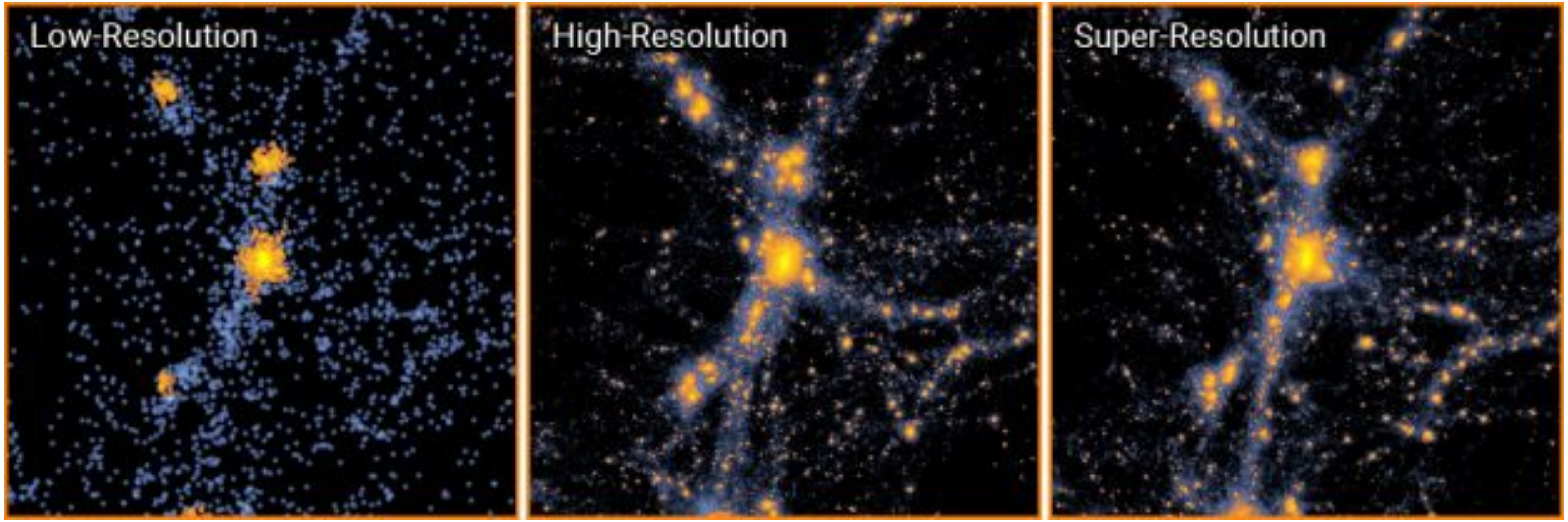
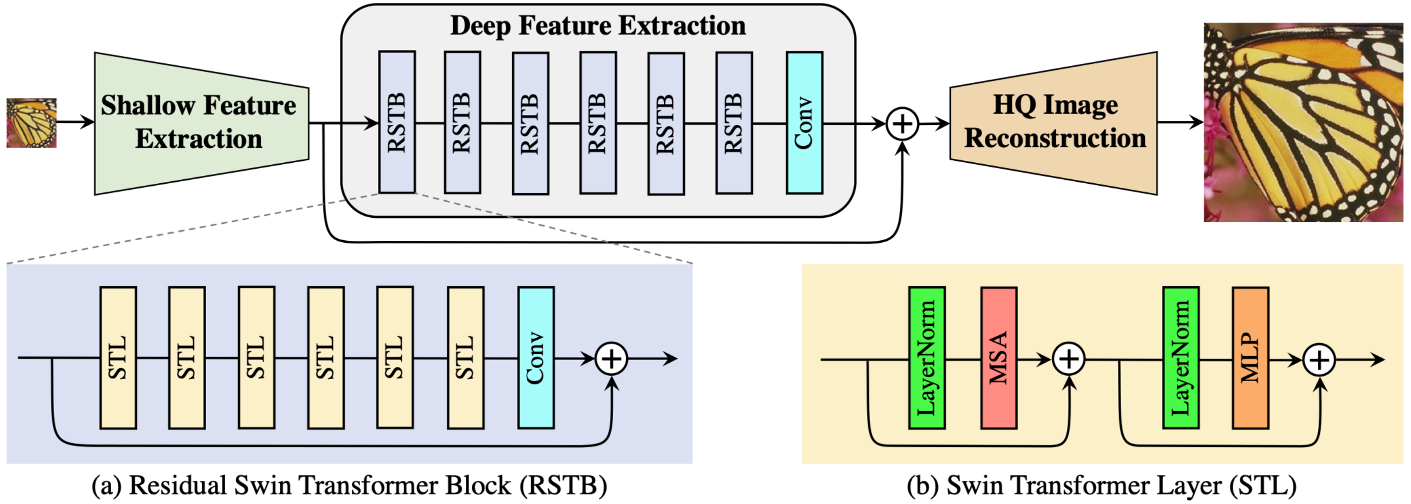
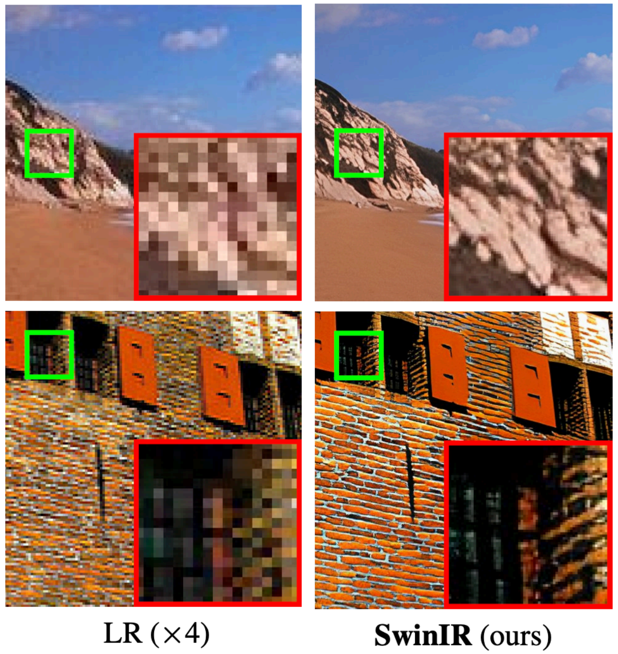


State-of-the-Art: Deep Neural Networks

- Deep neural networks (DNNs) are commonplace among the current state-of-the-art in SISR.
- SwinIR (Liang et al. 2021) is one of the current top performing SISR models.



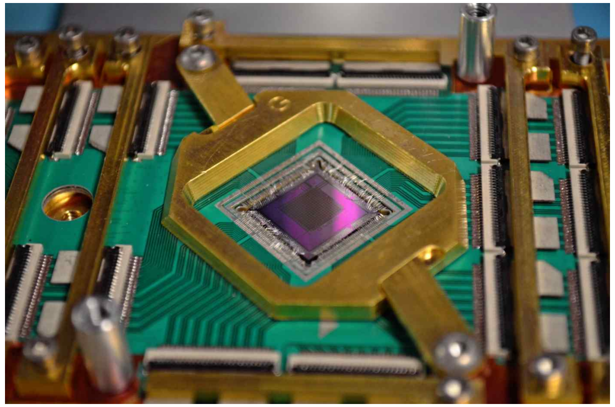
SwinIR architecture



SISR using SwinIR

Our Goal: Exploring Quantum Computing for SISR

- Quantum mechanics can be exploited to solve combinatorial optimization problems with exponential speed-up.
- Active area of research, in recent years implemented and demonstrated on quantum processing units (QPUs).



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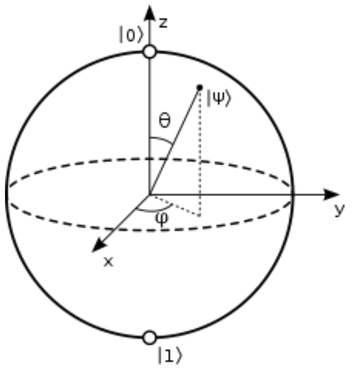
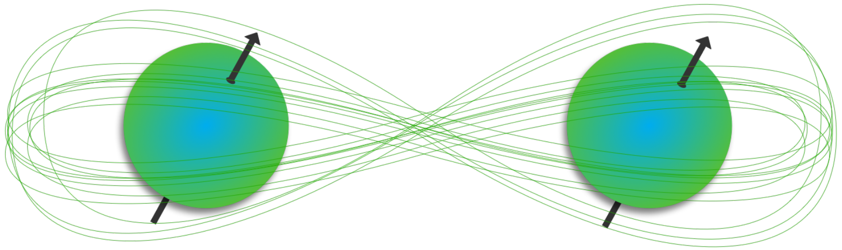
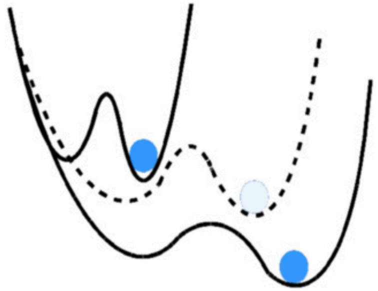


Superposition



Entanglement



Adiabatic Evolution

Adiabatic Quantum Computing: Context

In modern quantum computing, there are two types:

1) Universal gate quantum computing

2) **Adiabatic quantum computing (AQC)**

We focus on AQC, as it can increasingly be applied to solve practical computer vision problems.

An illustration of the AQC process (Zaech et al. 2022)

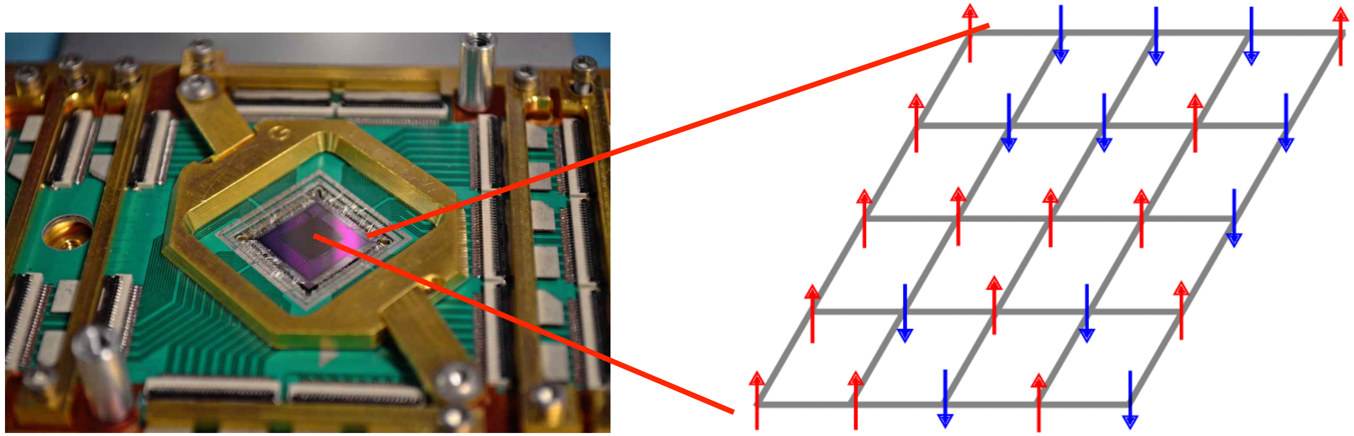
Adiabatic Quantum Computing: Problem Definition & Implementation

AQC solves a quadratic unconstrained binary optimization (**QUBO**) problem:

$$\underset{z}{\operatorname{argmin}}\, z^T Q z + b^T z$$

where $Q \in \mathbb{R}^{N\times N}$ contains quadratic coefficients, $b \in \mathbb{R}^N$ contains linear coefficients and $z \in \{0,1\}^N$ is a binary vector to be optimized.

The QUBO problem is embedded onto a physical lattice in a QPU then optimized by quantum annealing.



Our Approach: Finding a Traditional SISR Method

To use AQC, an appropriate problem formulation for SISR is required.

→ **Image Super-Resolution as Sparse Representation of Raw Image Patches** (Yang et al. 2008)

Training images and raw image patches extracted from them (Yang et al. 2008)

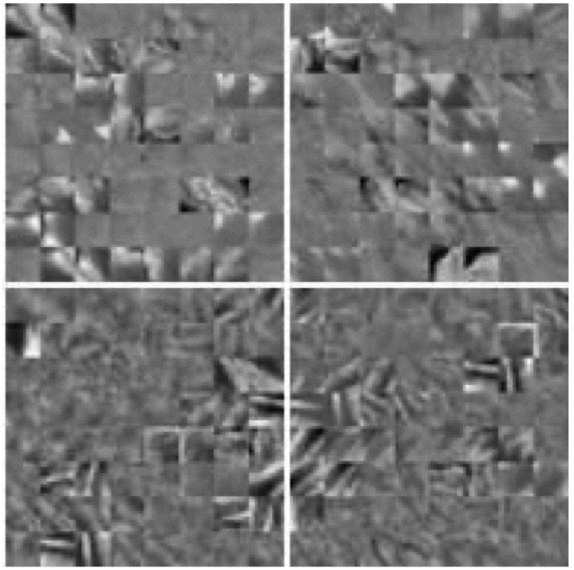
Our Approach: SISR via Sparse Representation

In the method of "SISR via sparse representation", HR images are constructed patch-wise, with each HR patch given by a sparse linear combination of raw image patches.

$$x = D_h \alpha^*$$

HR patch *Dictionary* *Sparse coefficients*

The atoms of D_h consist of image patches.



Raw image patches (Yang et al. 2008)

Our Approach: SISR via Sparse Representation

The sparse coefficients $\alpha*$ are found by solving a l_1 optimization based on a paired dictionary D_l.

$$x = D_h \alpha*$$

HR patch *HR Dictionary* *Sparse coefficients*

$$\alpha* = \text{argmin}_\alpha \, \|D_l \alpha - \tilde{y}\|_2^2 + \lambda \|\alpha\|_1$$

Sparse coefficients *LR Dictionary* *LR patch Feature Map*

Our Approach: Binary Sparse Coding

We then cast the l_1 optimization into binary form via $\alpha = \mu z$, where μ is a hyperparameter and $z \in \{0,1\}^N$ is the N-dimensional binary vector to be optimized in QUBO.

$$\alpha^* = \text{argmin}_\alpha \; ||D_l\alpha - \tilde{y}||_2^2 + \lambda||\alpha||_1$$

Sparse coefficients

LR Dictionary

LR patch Feature Map

$$\alpha^* = \mu \cdot \text{argmin}_z \; z^T Q z + b^T z \qquad Q = \mu D_l^T D_l$$

$$b = -2D_l^T \tilde{y} + \lambda \mathbf{1}_N$$

Sparse coefficients

QUBO problem to optimize z

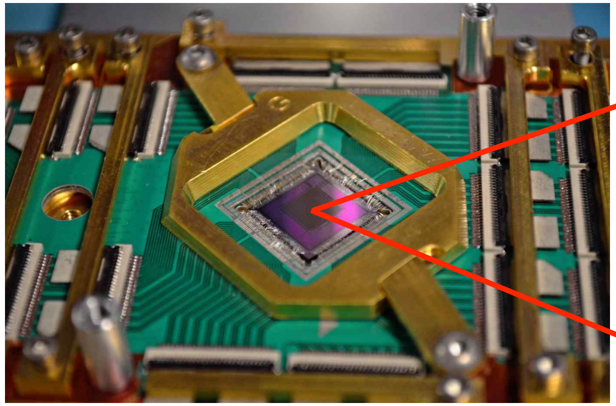
N-D vector of ones

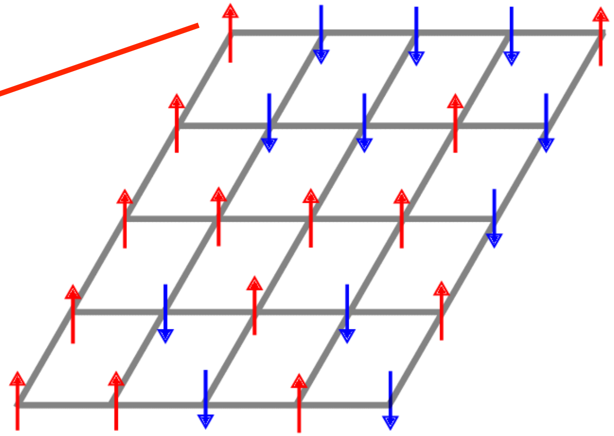
Our Approach: Binary Sparse Coding

$$\alpha^* = \mu \cdot \text{argmin}_z \; z^T Q z + b^T z$$

$$Q = \mu D_l^T D_l$$
$$b = -2D_l^T \tilde{y} + \lambda \mathbf{1}_N$$

With an appropriate QUBO formulation of binary sparse coding, *SISR via sparse representation* can now be implemented on QPUs.

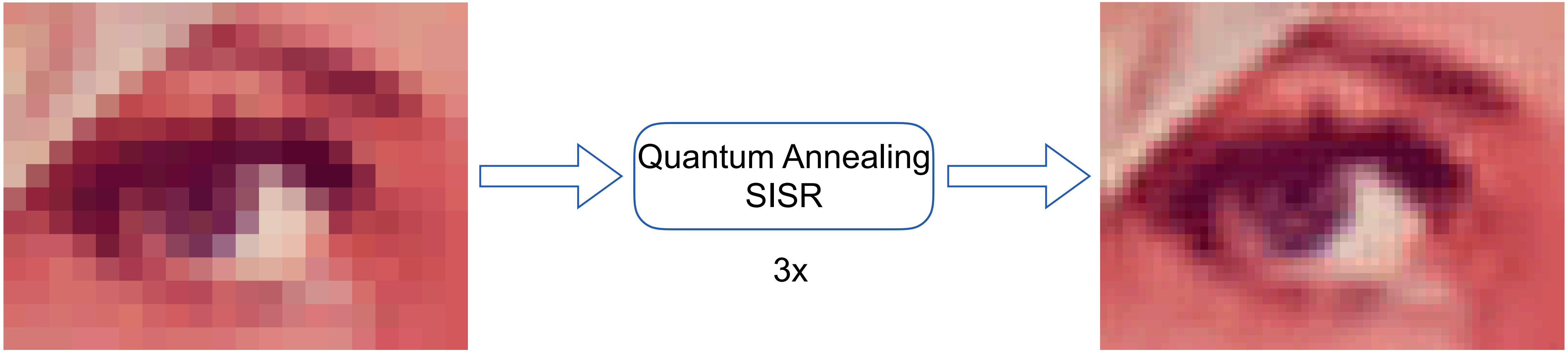




An illustration of an Ising model lattice in a QPU

Experiments: Training Details

- Training follows Yang et al. (2008). Evaluation on the “Lenna” image and Set5.
- Algorithms: 1) Lasso Regression (LR), 2) Classical Annealing (CA), 3) Quantum Annealing (QA).
- All algorithms carry out 3x upsampling.



3x

LR

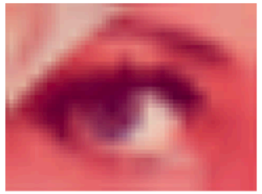
HR

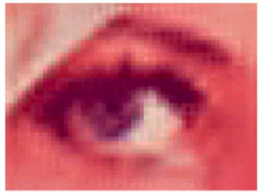
Experiments: PSNR Results

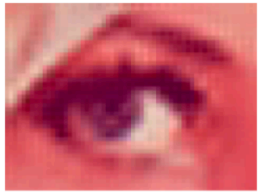
Model	PSNR		
	(a) Lenna reg. (dB)	(b) Lenna (dB)	(c) Set5 (dB)
Bicubic	28.31	30.62	29.35
Lasso Regress.	30.22	31.58	30.44
Classical Ann.	30.20	31.70	30.61
Quantum Ann.	30.19	31.70	30.61
SwinIR (DL)	**31.42**	**33.29**	**33.89**

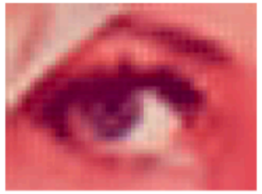

LR
(Downsampled Original)


HR
(Original)

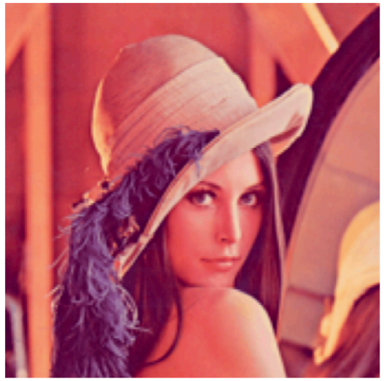

SR, PSNR=28.31
(Bicubic Interpolation)

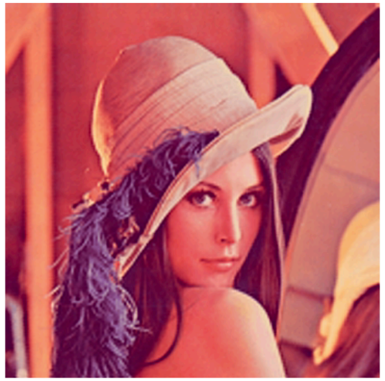

SR, PSNR=30.22
(Lasso Regression)


SR, PSNR=30.20
(Classical Annealing)


SR, PSNR=30.19
(Quantum Annealing)

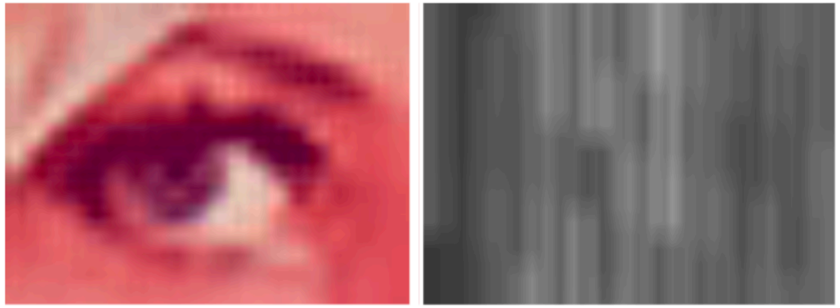
- CA and QA achieve the same accuracy.
- Annealing-based methods outperform bicubic interpolation and Lasso Regression on the full “Lenna" image and Set5.
- Performance of sparse coding approaches nevertheless fall short of state-of-the-art DNNs.


LR
(Downsampled Original)


SR, PSNR=31.70
(Quantum Annealing)

Summary

- Initial demonstration of quantum SISR with encouraging results.
- Evidence of superior sparse coding performance of CA and QA over conventional sparse coding in the SISR context.
- Algorithm design enables fast robust prediction, uncertainty estimation and improved performance over conventional sparse coding.
- Increased QPU access time can increase speed of QA by reducing classical computational loads.



SR, PSNR=30.19
(Quantum Annealing)

Uncertainty Map
(Entropy)

Visualization of an uncertainty map produced by computing the entropy of samples returned from a quantum annealer.