Xi Zhu, Wei Zhang, Yijie Li, Lauren J. O'Donnell, and Fan Zhang

Medical Image Computing and Computer Assisted Interventions (MICCAI)

2024

Goal of the paper:

Generation of dMRI using machine learning to enhance image quality while reducing acquisition costs and scanning time



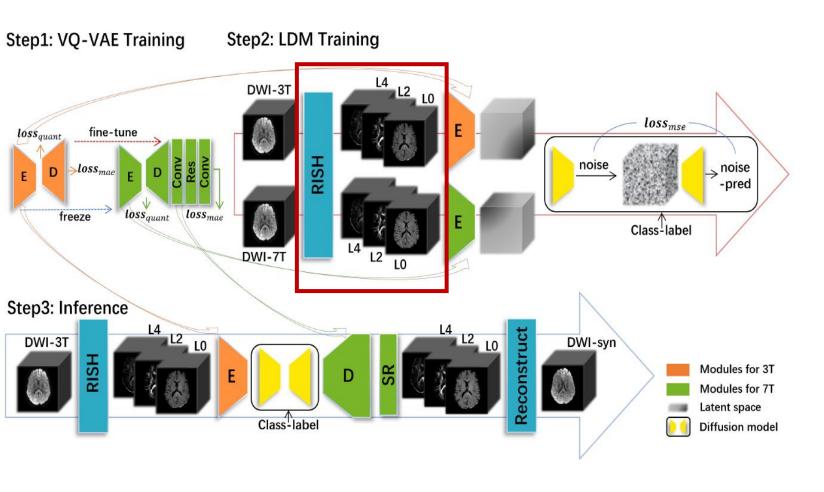
propose a novel generative approach to perform high quality dMRI generation using deep diffusion models

Diffusion model

a forward diffusion stage, where Gaussian noise is added to input data progressively

followed by a reverse diffusion stage aimed at gradually reverting the process to recover original input

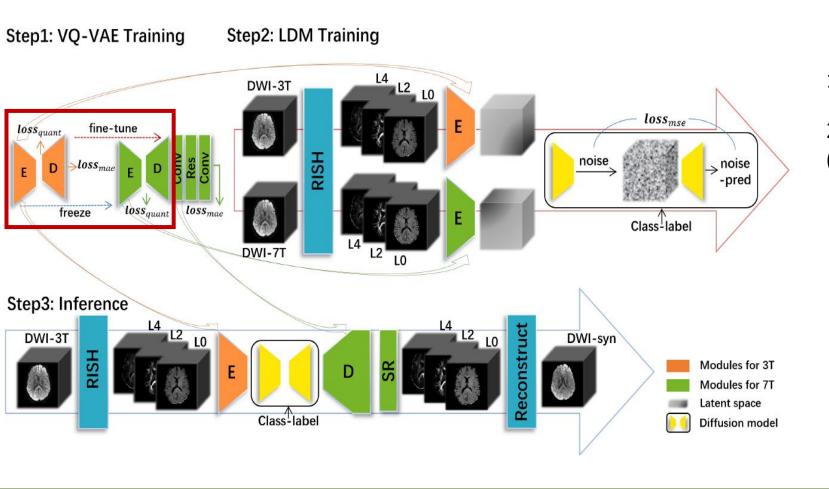
Model architecture



Training Time

1. Computing *Rotation Invariant Spherical Harmonic (RISH)* features in different orders for a compact representation of input 3T and 7T dMRI

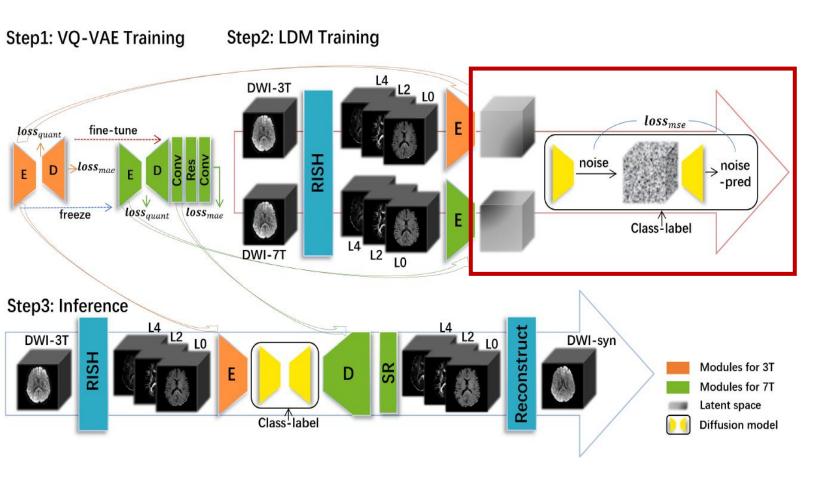
Model architecture



Training Time

- 1. Computing RISH features
- 2. Vector Quantised-Variational AutoEncoder (VQ-VAE)

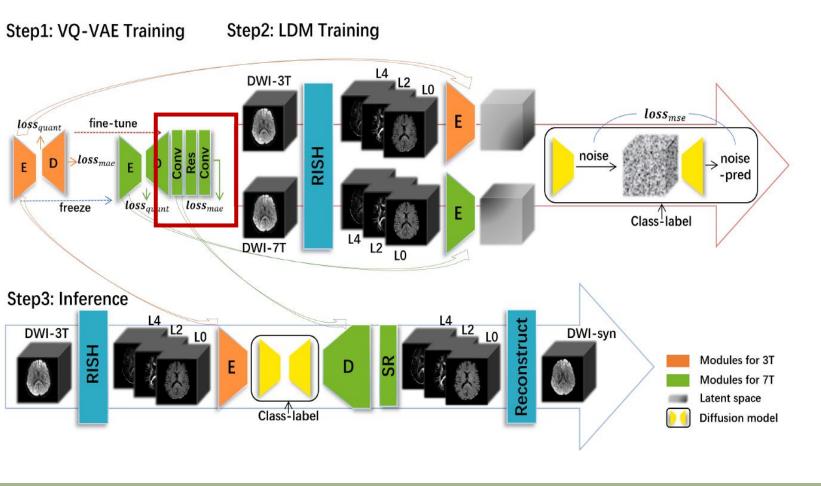
Model architecture



Training Time

- 1. Computing RISH features
- 2. Vector Quantised-Variational AutoEncoder (VQ-VAE)
- 3. VQ-VAE's encoder outputs used as inputs for diffusion model

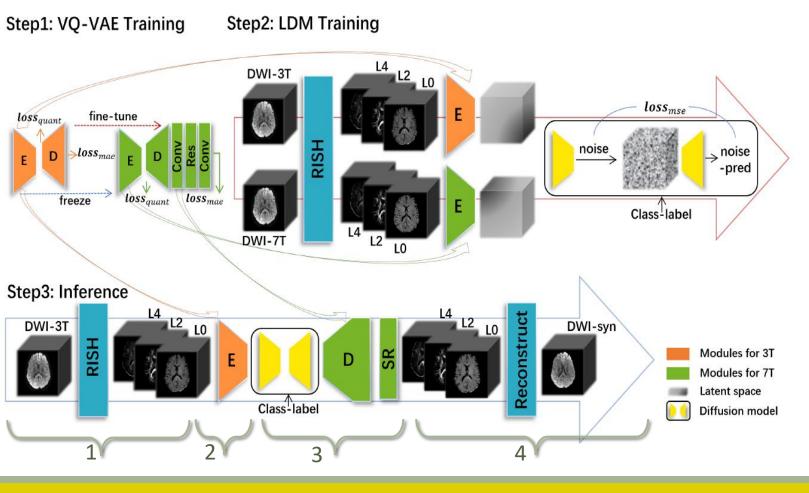
Model architecture



Training Time

- 1. Computing RISH features
- 2. Vector Quantised-Variational AutoEncoder (VQ-VAE)
- 3. VQ-VAE's encoder outputs used as inputs for diffusion model
- 4. train the super-resolution module using the dataset generated by LDM

Model architecture



Inference Time

- 1. RISH features of 3T test data
- 2. Using 3T encoder to encode into latent space
- 3. Diffusion model followed by decoder and super resolution model
- 4. Generating 7T-like RISH features to reconstruct a high quality 7T dMRI

Dataset

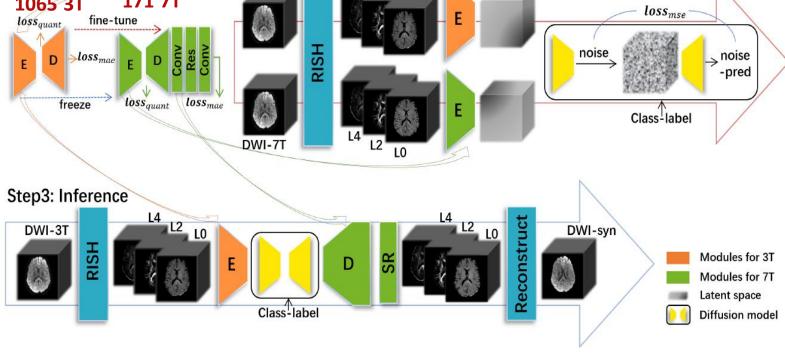


- 171 subjects has both 3T and 7T data 894 subjects has only 3T data

Project (HCP) including:

1065 subjects from Human Connectome

- Every test set includes 17 test subjects



Results

Table 1. Comparison of NMSE and SSIM in RISH and FA across different methods.

NMSE↓:	RISH_L0	RISH_L2	RISH_L4	FA
CNN	0.126 ± 0.014	0.143 ± 0.011	0.495 ± 0.107	0.053 ± 0.007
GAN	0.129 ± 0.029	0.427 ± 0.051	1.652 ± 0.360	0.118 ± 0.009
Diffusion	0.105 ± 0.026	$\boldsymbol{0.102 \pm 0.017}$	$\boldsymbol{0.158 \pm 0.031}$	0.044 ± 0.008
SSIM↑:				
CNN	0.000 1.0.000			
CIVIN	0.889 ± 0.008	0.959 ± 0.006	0.956 ± 0.016	0.958 ± 0.006
GAN		0.959 ± 0.006 0.893 ± 0.010		

Results

CNN: a loss of contrast information between different regions **X**

GAN: fails to preserve some structural details in higher order RISH features X

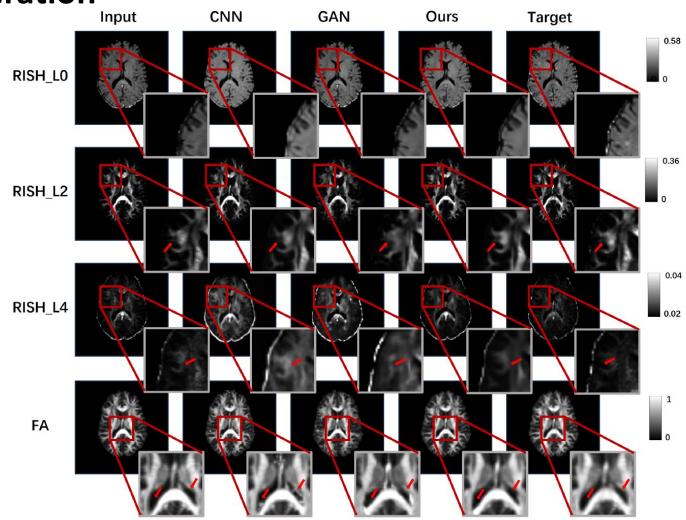


Fig. 2. Results for the RISH features and FA generated by different methods.

Results

- 1. Trained with 7T dataset without fine-tuning
- 2. Trained without super-resolution module, instead using a B-spline interpolation to upscale 3T to resolution of 7T

Table 2. Ablation study results

	Fine-tuning	Super-resolution	NMSE↓	SSIM↑
1.	-	-	0.046 ± 0.008	0.962 ± 0.008
2.	\checkmark	-	0.044 ± 0.008	0.966 ± 0.007
	✓	\checkmark	0.042 ± 0.004	$\boldsymbol{0.967 \pm 0.007}$

Conclusion

- ✓ The application of latent diffusion models to dMRI generation is new.
- ✓ The integration of new feature extraction with the diffusion model in training is interesting.

- × Dependent on the availability of both 3T and 7T dMRI data for training
- × High computational costs due to using diffusion model, VQ-VAE and super-resolution module
- × Generalizability to other datasets

Thank you