CUNSB-RFIE: Context-aware Unpaired Neural Schrödinger Bridge in Retinal Fundus Image Enhancement

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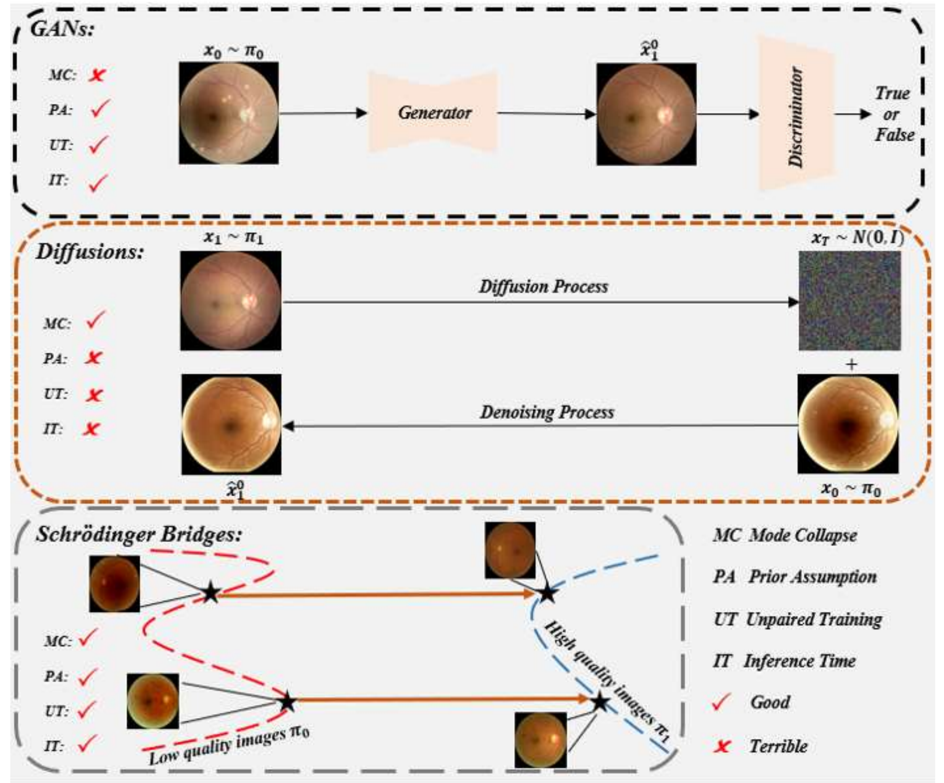
Introduction

Retinal fundus image enhancement

- **Why:** Enhancing retinal image quality is essential to ensure accurate diagnosis of ocular diseases by reducing noise and revealing critical clinical details like blood vessels and lesions
- **Input:** low-quality, noisy retinal images (illumination, spot artifacts, and blurring)
- **Output:** High-quality retinal images counterparts
- **How:** Learning the **Schrödinger Bridge (SB)** between different image domains

Motivation

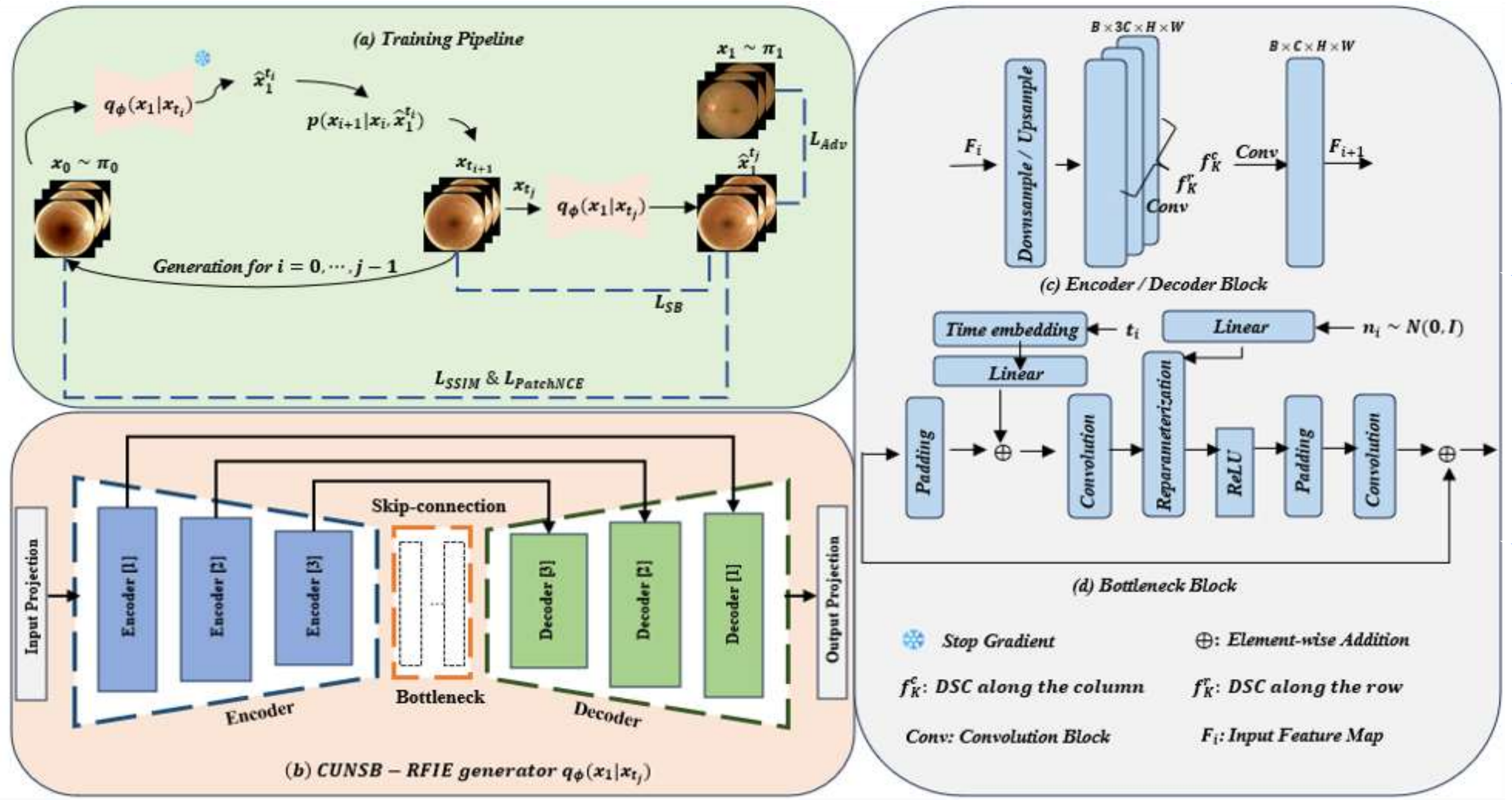


- **GANs:**
  1. stability vs diversity / quality
- **Diffusions:**
  1. Require paired data
  2. Prior Gaussian assumptions
  3. Slower inference times
- **SB:**
  No limitations

Contribution

- **SB-Based Method**: Eliminates prior assumptions and reduces inference steps while retaining diffusion benefits
- **CUNSB-RFIE**: Combines Dynamic Snake Convolution (DSC), PatchNCE, and SSIM for contextual preservation.
- **Extensive Validation**: Outperforms multiple baselines

Proposed Method



CUNSB –RFIE Framework

Static Formulation and Self-similarity

★ $$\mathbb{Q}^{SB}_{t_a t_b} = \underset{\gamma \in \Pi(\mathbb{Q}_{t_a}, \mathbb{Q}_{t_b})}{\arg\min} \mathbb{E}_{(\boldsymbol{x}_{t_a}, \boldsymbol{x}_{t_b}) \sim \gamma}[\|\boldsymbol{x}_{t_a} - \boldsymbol{x}_{t_b}\|^2] - 2\tau(t_b - t_a)H(\gamma)$$

★ $$p(\boldsymbol{x}_t | \boldsymbol{x}_{t_a}, \boldsymbol{x}_{t_b}) \sim N(\boldsymbol{x}_t; \mu_{t_a,t_b}, \sigma_{t_a,t_b})$$

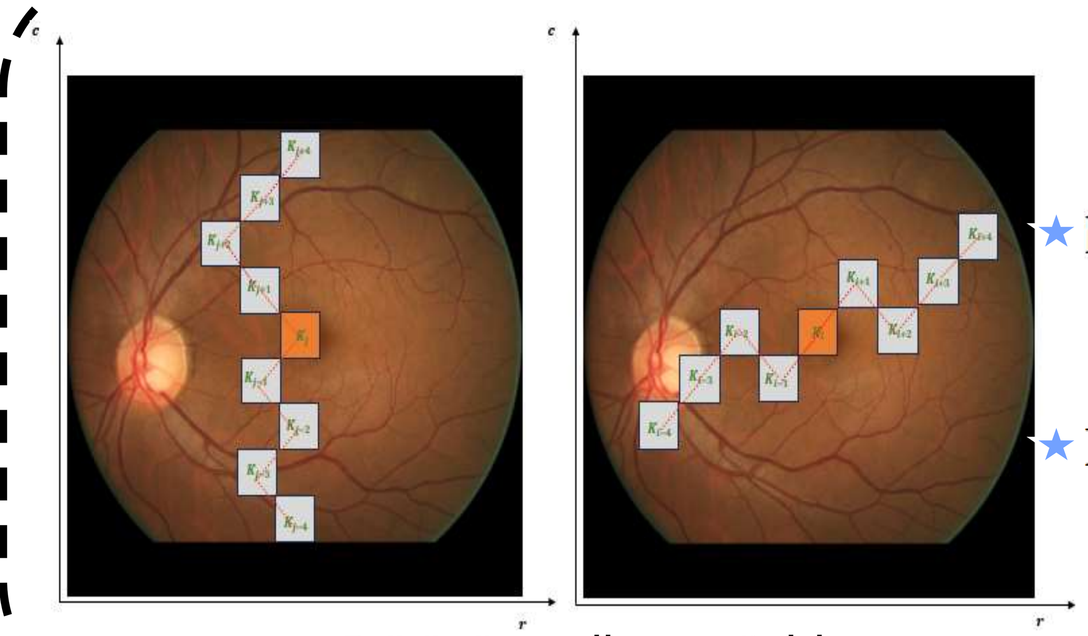
$$\begin{cases} \mu_{t_a,t_b} = s(t)\boldsymbol{x}_{t_b} + (1 - s(t))\boldsymbol{x}_{t_a} \\ \sigma_{t_a,t_b} = s(t)(1 - s(t))\tau(t_b - t_a)\boldsymbol{I} \end{cases}$$

Schrödinger Bridge Learning

★ $$\min_{\phi} \quad \mathbb{L}_{SB}(\phi, t_i) := \mathbb{E}_{q_\phi(\boldsymbol{x}_{t_i}, \boldsymbol{x}_1)}[\|\boldsymbol{x}_{t_i} - \boldsymbol{x}_1\|^2] - 2\tau(1 - t_i)H(q_\phi(\boldsymbol{x}_{t_i}, \boldsymbol{x}_1))$$

$$\text{s.t.} \quad \mathbb{L}_{Adv}(\phi, t_i) := \mathbb{D}_{\mathbb{KL}}(q_\phi(\boldsymbol{x}_1) \| p(\boldsymbol{x}_1)) = 0$$

$$\min_{\phi} \mathbb{L}(\phi, t_i) := \mathbb{L}_{Adv}(\phi, t_i) + \lambda_{SB}\mathbb{L}_{SB}(\phi, t_i)$$



DSC Coordinate Grids

Tubular Feature Capture

★ $$\mathbb{K}_{i \pm z} = \begin{cases} (\boldsymbol{r}_{i+z}, \boldsymbol{c}_{i+z}) = (\boldsymbol{r}_i + z, \boldsymbol{c}_i + \Sigma_i^{i+z}\Delta \boldsymbol{c}) \\ (\boldsymbol{r}_{i-z}, \boldsymbol{c}_{i-z}) = (\boldsymbol{r}_i - z, \boldsymbol{c}_i + \Sigma_{i-z}^{i}\Delta \boldsymbol{c}) \end{cases}$$

★ $$\mathbb{K}_{j \pm z} = \begin{cases} (\boldsymbol{r}_{j+z}, \boldsymbol{c}_{j+z}) = (\boldsymbol{r}_j + \Sigma_j^{j+z}\Delta \boldsymbol{r}, \boldsymbol{c}_j + z) \\ (\boldsymbol{r}_{j-z}, \boldsymbol{c}_{j-z}) = (\boldsymbol{r}_j + \Sigma_{j-z}^{j}\Delta \boldsymbol{r}, \boldsymbol{c}_j - z) \end{cases}$$

Final Objective

★ $$\mathbb{L}_{SSIM}(\phi, t_i) := (\mathbb{L}^{gen}(\boldsymbol{x}_{t_i}, \hat{\boldsymbol{x}}_1^{t_i}) + \mathbb{L}^{idt}(\boldsymbol{x}_1, \hat{\boldsymbol{x}}_1^1))/2$$

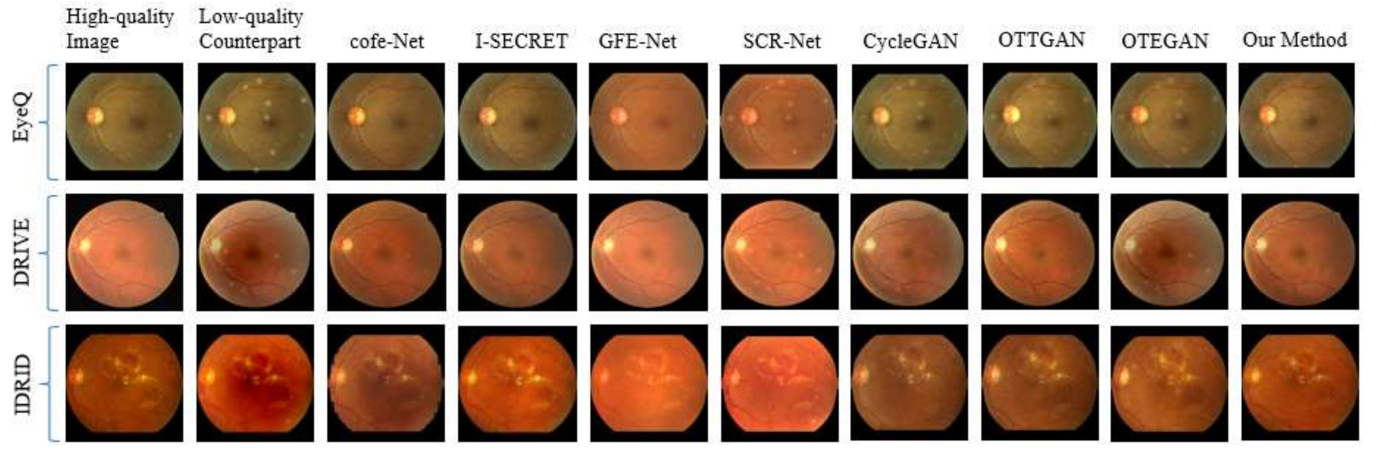
$$\begin{cases} \mathbb{L}^{gen} := 1 - SSIM(\boldsymbol{x}_{t_i}, \hat{\boldsymbol{x}}_1^{t_i}) \\ \mathbb{L}^{idt} := 1 - SSIM(\boldsymbol{x}_1, \hat{\boldsymbol{x}}_1^1) \end{cases}$$

★ $$\mathbb{L}_{CUNSB}(\phi, t_i) := \mathbb{L}_{Adv}(\phi, t_i) + \lambda_{SB}\mathbb{L}_{SB}(\phi, t_i) + \lambda_S\mathbb{L}_{SSIM}(\phi, t_i) + \lambda_P\mathbb{L}_{PatchNCE}(\phi, t_i)$$

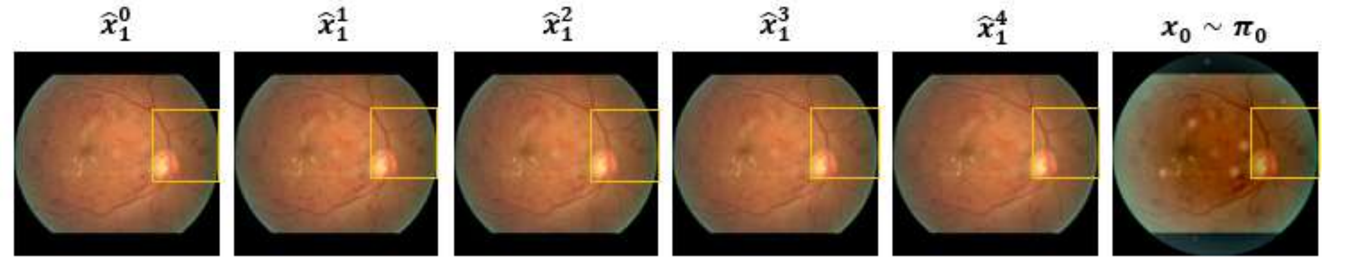
Results

	Method	EyeQ		IDRID		DIRVE	
		SSIM ↑	PSNR↑	SSIM	PSNR	SSIM	PSNR
Supervised Methods	cofe-Net [34]	0.880	17.25	0.65	19.07	0.66	19.11
Unsupervised Methods	I-SECRET [3]	0.884	14.84	0.756	18.40	0.669	18.75
	GFE-Net [18]	0.80	18.68	0.631	19.21	**0.715**	15.14
	SCR-Net [17]	0.796	18.86	0.616	19.51	0.668	18.50
	CycleGAN [48]	0.878	22.93	0.764	21.01	0.653	21.59
	OTTGAN [42]	0.895	23.25	0.755	20.94	0.637	20.73
	OTEGAN [51]	**0.898**	23.51	0.687	18.20	0.601	17.96
	Ours	0.858	**27.61**	**0.768**	**21.92**	0.649	**22.07**

Method	Vessel Segmentation				EX			HE		
	AUC ↑	PR ↑	SE ↑	SP ↑	AUC	PR	Jaccard ↑	AUC	PR	Jaccard
cofe-Net [34]	0.911	0.766	**0.624**	0.977	0.898	0.257	0.190	0.807	0.083	0.076
I-SECRET [3]	0.878	0.695	0.531	0.977	0.900	0.257	0.193	0.821	0.080	0.083
GFE-Net [18]	0.911	0.762	0.619	0.977	0.904	0.296	0.205	0.809	0.087	0.069
SCR-Net [17]	0.904	0.748	0.599	0.977	0.906	0.259	0.181	0.830	0.118	0.107
CycleGAN [48]	0.885	0.718	0.580	0.975	0.906	0.379	0.179	0.809	0.123	0.101
OTTGAN [42]	0.896	0.740	0.592	0.977	0.928	0.438	0.239	0.872	0.197	**0.140**
OTEGAN [51]	0.908	0.764	0.623	0.977	**0.953**	**0.513**	**0.338**	**0.882**	**0.242**	0.133
Ours	**0.918**	**0.771**	0.607	**0.979**	0.921	0.327	0.215	0.856	0.122	0.115



Smooth Influence



Contact

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GitHub: https://github.com/Retinal-Research/CUNSB-RFIE