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CAS-GAN for Contrast-free Angiography Synthesis

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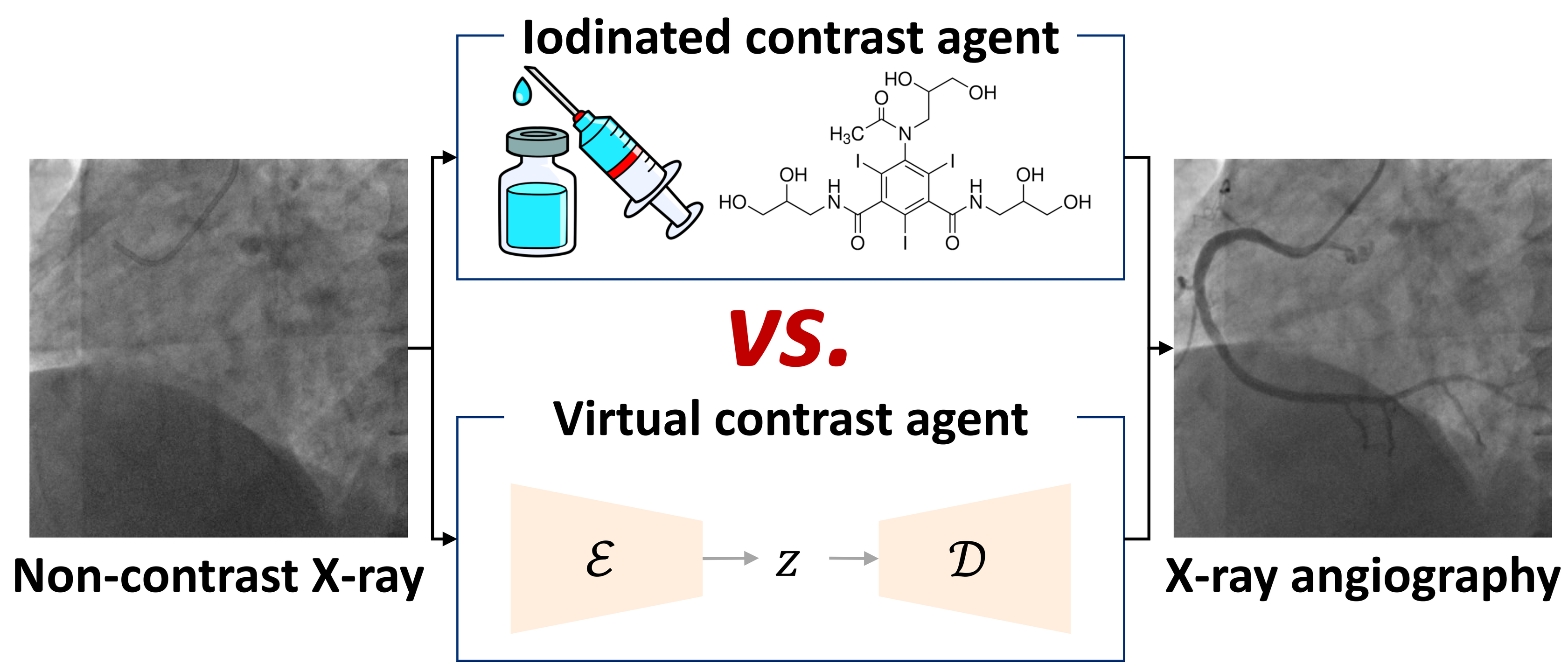
I. Abstract

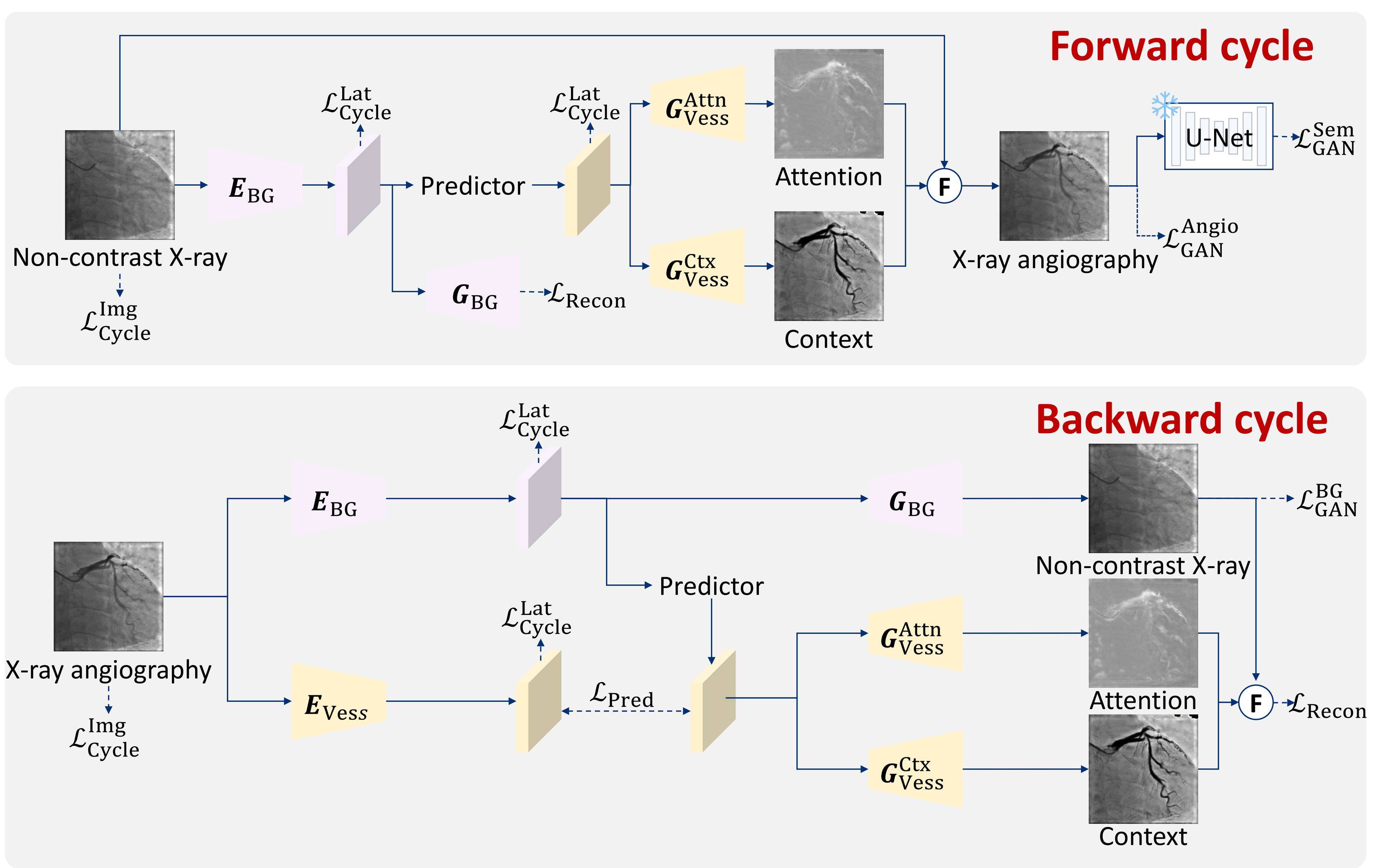
Iodinated contrast agents are widely utilized in numerous interventional procedures, yet posing substantial health risks to patients. This paper presents CAS-GAN, a novel GAN framework that serves as a “virtual contrast agent” to synthesize X-ray angiographies via disentanglement representation learning and vessel semantic guidance, thereby reducing the reliance on iodinated contrast agents during interventional procedures. Specifically, our approach disentangles X-ray angiographies into background and vessel components, leveraging medical prior knowledge. A specialized predictor then learns to map the interrelationships between these components. Additionally, a vessel semantic-guided generator and a corresponding loss function are introduced to enhance the visual fidelity of generated images. Experimental results on the XCAD dataset demonstrate the state-of-the-art performance of our CAS-GAN, achieving a FID of 5.87 and a MMD of 0.016. These promising results highlight CAS-GAN's potential for clinical applications.

II. Motivation

- Iodinated contrast agents pose significant health risks for patients, including allergic reactions (***Lancet Discovery Science***, 2018) and acute kidney injury (***Nature Reviews Nephrology***, 2017).
- Generative models can synthesis photo realistic images based on specific constrain (***Nature Medicine***, 2024).



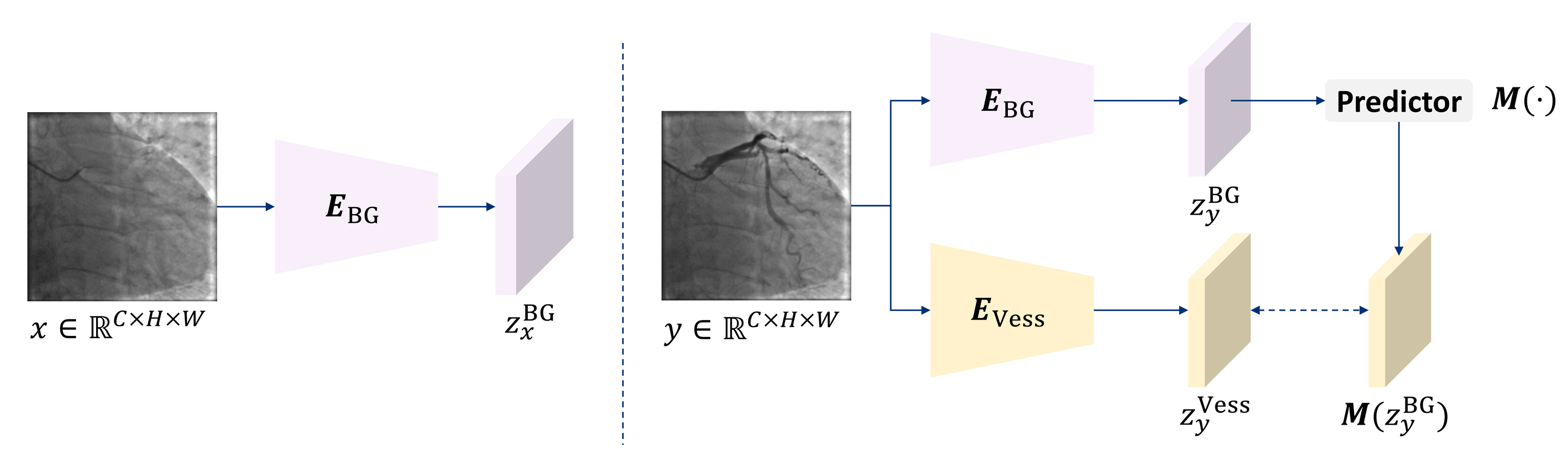
III. Pipeline of CAS-GAN



CAS-GAN is designed to learn an unpaired image translation function. To address the inherent challenges of this under-constrained translation, we adopt a cycle-consistency approach. Unlike conventional methods focused on style mappings, we propose a **disentanglement representation learning approach** (**Sec. IV (a)**) and **vessel semantic-guided generation process** (**Sec. IV (b)**) to enhance fidelity of generated images.

IV. Methods

(a) Disentanglement representation learning



- **Disentanglement encoding**

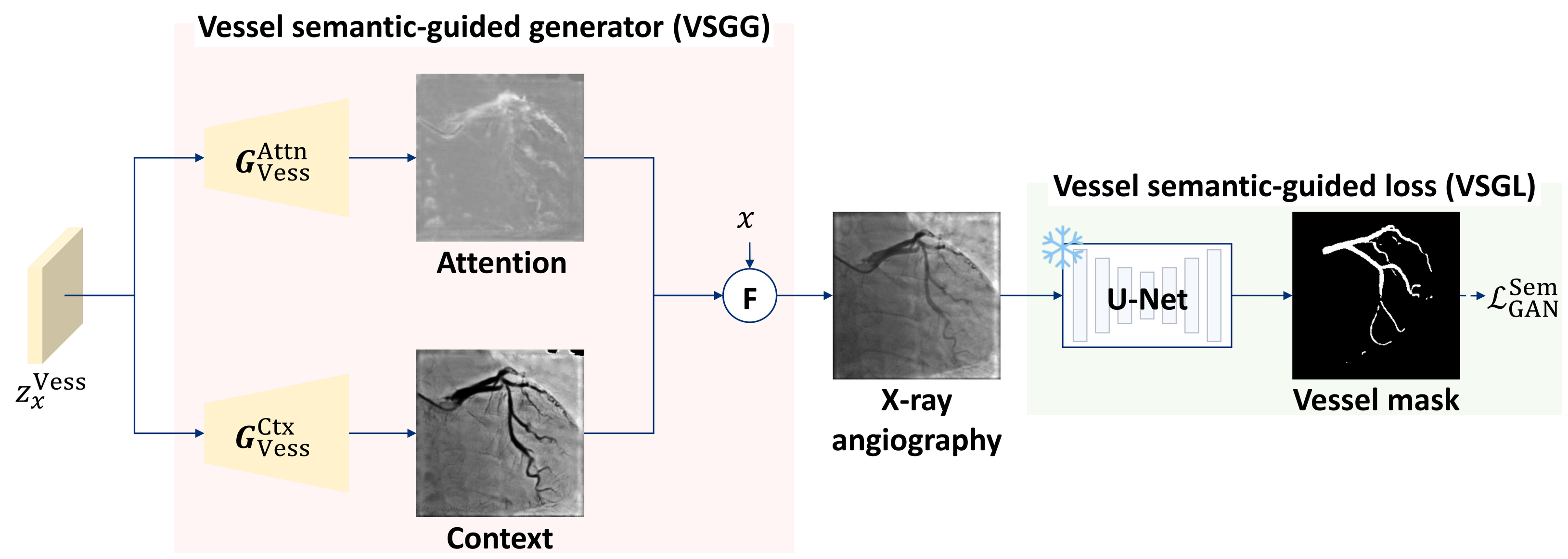
  Background representations: $z_x^{BG} = \boldsymbol{E}_{BG}(x)$, $z_y^{BG} = \boldsymbol{E}_{BG}(y)$

  Vessel representations: $z_x^{Vess} = \boldsymbol{M}(z_x^{BG})$, $z_y^{Vess} = \boldsymbol{E}_{Vess}(x)$

- **Explicitly formulating the relationship between z^{BG} and z^{Vess}**

  Prediction loss: $\mathcal{L}_{Pred} = \mathbb{E}_{y\sim Y}\left\{\left|M(z_y^{BG}) - z_y^{Vess}\right|_1\right\}$

(b) Vessel semantic-guided generation



- **Generator**

$$A_g = \boldsymbol{G}_{Vess}^{Attn}\left[\boldsymbol{M}(z_x^{BG})\right],\ C_g = \boldsymbol{G}_{Vess}^{Ctx}\left[\boldsymbol{M}(z_x^{BG})\right]$$

$$y_g = x \odot (1 - A_g) + C_g \odot A_g$$

- **Loss function**

$$s = \mathrm{UNet}(y),\ s_g = \mathrm{UNet}(y_g)$$

$$\mathcal{L}_{GAN}^{Sem} = \mathbb{E}_{s\sim S}[\log \boldsymbol{D}_{Sem}(s)] + \mathbb{E}_{s_g\sim S_g}\left[\log\left(1 - \boldsymbol{D}_{sem}(s_g)\right)\right]$$

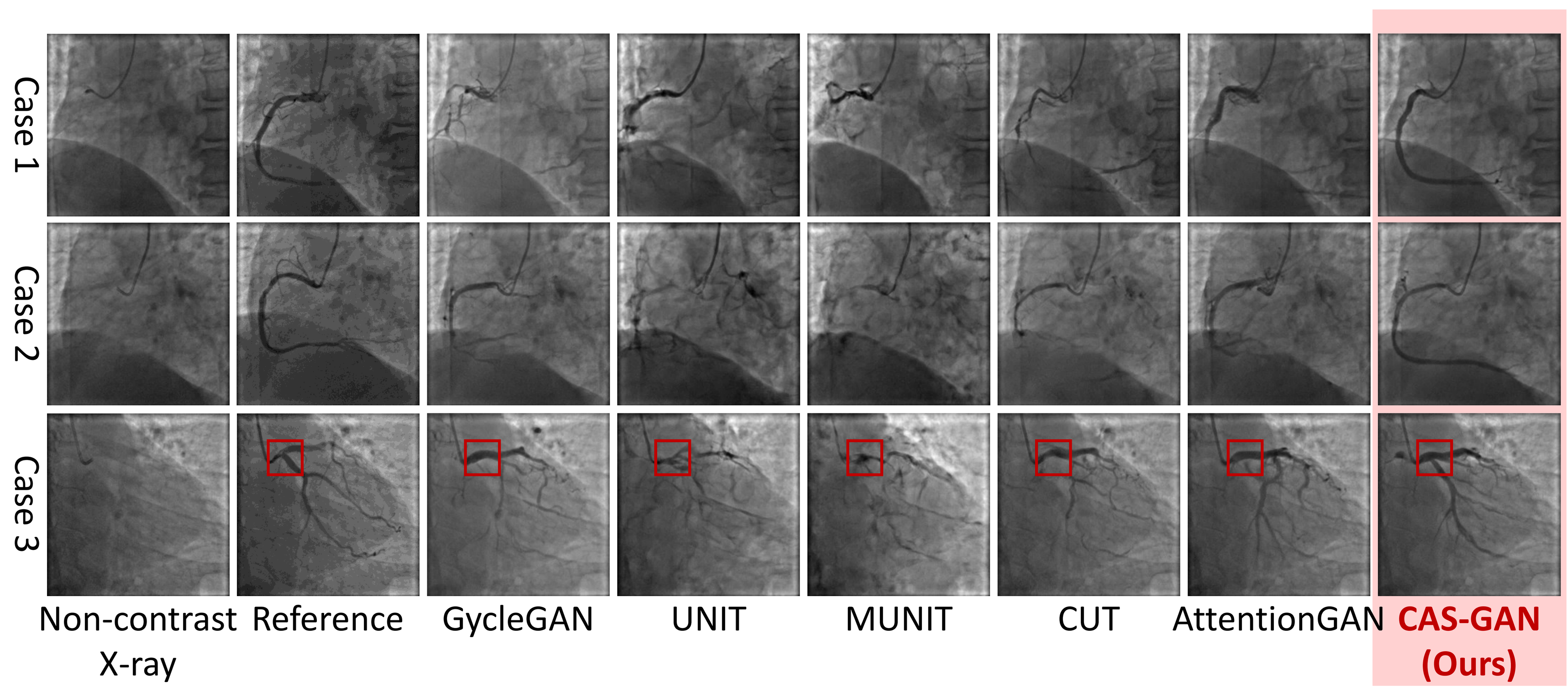
V. Experiments

Table I. Quantitative results with SOTAs.

Method	FID ↓	MMD (× 10) ↓
CycleGAN [ICCV’17]	6.54	0.28
UNIT [NeurIPS’17]	9.99	<u>0.22</u>
MUNIT [ECCV’18]	8.87	0.33
CUT [ECCV’20]	7.09	0.26
AttentionGAN [TNNLS’21]	<u>6.34</u>	0.31
QS-Attn [CVPR’22]	7.20	0.24
StegoGAN [CVPR’24]	10.80	2.26
CAS-GAN **[Ours]**	**5.87**	**0.16**

Table II. Effects of several designs.

Index	DRL	VSGG	VSGL	FID ↓	Δ
1				7.14	+1.27
2			✓	8.59	+2.72
3		✓		6.57	+0.70
4		✓	✓	5.98	+0.11
5	✓			6.87	+1.00
6	✓		✓	6.70	+0.83
7	✓	✓		5.93	+0.06
8	✓	✓	✓	5.87	–



VI. Conclusion & Future work

- We proposed a novel method for contrast-free X-ray angiography synthesis. This method offers a promising perspective for reducing the reliance on contrast agents during vascular interventional procedures.
- We introduced a disentanglement representation learning approach and a vessel semantic-guided generation process to ensure the visual fidelity of generated X-ray angiographies.
- In future works, the method will be validated on a large-scale dataset. Additionally, downstream applications will be conducted, verifying the feasibility of the method in vivo animal experiments.